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THE IMPACT OF BODY WEIGHT ON OCCUPATIONAL MOBILITY AND CAREER DEVELOPMENT*

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This article examines the relationship between individuals' weight and employment decisions over the life cycle. I estimate a dynamic stochastic model of individuals' annual choices of occupation, hours worked, and schooling. Evidence suggests 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. I simulate a hypothetical antidiscrimination policy treating obese workers as a protected class. Although such a policy would reduce gaps in occupational attainment, it would have little effect on the observed divergence in wages between obese and nonobese workers.

1. INTRODUCTION

How does body weight affect employment behavior and wages over the life cycle? We know obesity yields high costs in the workplace.[2] Estimates place annual workplace productivity costs of obesity between \$12 and \$30 billion. Although obese workers miss 15%–50% more work time than healthy weight workers, 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 affects the expected present discounted value of employment decisions not only by affecting contemporaneous wages and utility but also expected future wages and labor market opportunities.

The workplace costs of high body weight are inherently dynamic and vary by occupation. Studies have shown that obesity leads to difficulty managing professional interpersonal relationships and reduces stamina when performing physical tasks.[3] Although lower productivity affects wages, difficulties with certain job requirements may yield additional nonmonetary costs that also 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 heavier individuals. Differences between occupations in the expected 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,

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

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

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.

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. I formulate and estimate a dynamic discrete choice model where body weight affects both the distribution of wage offers and nonmonetary costs of each employment alternative, and employment decisions subsequently affect weight. Although the model therefore treats body weight as endogenous, it does so in a limited sense. Individuals do not choose body weight per se, but their body weight evolves as a consequence of the individuals' history of employment decisions.[4] Both the model and empirics follow in the occupational choice tradition of Keane and Wolpin (1997), Lee (2005), Lee and Wolpin (2006), Kambourov and Manovskii (2009), Sullivan (2010), and Baird (2014). I construct indices of the intensity of mental, physical, and social job requirements for each occupation to examine how job requirements affect the wage and nonmonetary costs of body weight. I estimate the parameters governing the individual's decision-making process using data from the National Longitudinal Survey of Youth, 1979 cohort.

This is the first article to examine differences in earnings and occupational attainment on the basis of body weight in a dynamic discrete occupational choice framework. Dynamic stochastic occupational choice models have been utilized to examine gender gaps in wages and occupational attainment (e.g., Altug and Miller, 1998; Flabbi, 2010; Eckstein and Lifshitz, 2011; Gayle and Golan, 2012; Yamaguchi, 2013) and similar black–white gaps (e.g., Keane and Wolpin, 2000; Bowlus and Eckstein, 2002; Lehmann, 2013). However, much of the existing literature on the relationship between body weight and employment outcomes has used static methods and examined contemporaneous cross-occupation "wage penalties" for body weight (e.g., Pagan and Davila, 1997; Cawley, 2004; Han et al., 2009; Johar and Katayama, 2012).[5] When occupation has been considered, it is usually as a control variable or mediating factor in the associative relationship between weight and mean wages. To the extent that body weight increases friction when transitioning into certain occupations, treating occupation as a control excludes an important mechanism by which body weight can affect wages.

This article also contributes to a growing literature where job requirements are incorporated into dynamic models as a determinant of occupational choice (Sanders, 2010; Yamaguchi, 2012) and the literature on how one's employment behavior affects one's health (e.g., King et al., 2001; Lakdawalla and Philipson, 2002; Courtemanche, 2009; Kelly et al., 2014, Ravesteijn et al., 2014). Additionally, this article incorporates prospective wage differentials into a single-agent occupational choice framework. As Coate and Loury (1993) show, anticipated wage differentials can affect the formation of human capital, which affects subsequent wages. Theoretically, the model seeks to merge Mincer (1958), Ben-Porath (1967), and Becker (1957). The structure of this model closely resembles Keane and Wolpin (1997) and Sullivan (2010), focusing on how current and expected future monetary and nonmonetary costs affect individuals' decisions over the life cycle. There is also a small methodological contribution to the literature on dynamic models of occupational choice regarding the distribution of unobserved wages. I estimate the full distribution of wages inside the model using conditional density estimation (CDE; Gilleskie and Mroz, 2004) instead of imposing a parametric distribution on wages. Additionally, CDE allows the marginal effect of explanatory variables to vary over the support of the dependent variable. This feature is useful given that Kline and Tobias (2008) and Johar and Katayama

[4] The purpose of this article 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 instead of modeling change in body weight as a choice.

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

(2012) have shown that the relationship between body weight and wages varies over the support of wages.

The results illustrate the short-term versus long-term consequences of high body weight on wages and career paths. Consistent with earlier work, I do not find large, direct contemporaneous wage penalties for body weight for men.[6] However, the relatively small effects of weight on wages at the conditional mean mask heterogeneous effects of weight over the distribution of wages. Although there is little to no effect of body weight on wages at or below the median wage, there are larger effects in the upper quartile of wages. Additionally, high body weight presents nontrivial barriers to occupational mobility and inhibits wage growth over the life cycle. Results indicate that one weight class (35 pounds on a 6-foot male) leads to higher switching costs ($6,200 at the mean wage, per 5 body mass index [BMI] points) when transitioning into professional and managerial occupations. These costs affect early and mid-career choices, leading to differences in human capital and subsequent wages. Individuals of high body weight are also found to earn lower returns to experience in white-collar occupations and face lower wages and higher nonmonetary costs in socially intensive jobs.[7] I use semiparametric 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 quantiles of the wage distribution. The combination of these results indicates that body weight is a significant impediment to career progress, particularly in white-collar occupations.

Using the estimated parameters of the model, I conduct several counterfactual simulations to evaluate both hypothetical policies and the importance of changing economic conditions. Although much of the literature on body weight and wages examines the extent to which observed wage differentials are driven by "discrimination," the first simulation takes a slightly different tack. Supposing that obese workers were made a protected class, what parameters would that policy affect and how would such a policy change gaps in wages and occupational choice frequencies? Results indicate that such a policy would reduce differences in occupational choice frequencies but have a minimal effect on wages.

Second, a separate literature has examined the effects of the built environment on body weight.[8] I examine how changes in the built environment and relative food prices have affected wages, and under the neoclassical perspective that wages are a function of productivity, average productivity of labor. Results indicate that changes in the built environment have reduced wages by 2% over the life cycle, which is approximately 20% of the effect from another simulation of a five-point increase in BMI at age 17. To illustrate the compounding, dynamic effects of body weight on wages and employment decisions, I simulate the effects of a considerable (5 BMI points) exogenous weight reduction on a 35-year-old individual. Although instantaneous effects are small, the dynamic effects are considerably larger. Relative to the baseline, the 45-year-old individual who experienced an exogenous shock at age 35 is nearly 10% more likely to be in a managerial occupation and the individual's overall expected wage increases by 10%. In summary, I find that although contemporaneous direct wage penalties for body weight for most workers are small, high body weight presents significant long-term costs to workers over the life cycle. Together, these results indicate that reducing adolescent obesity among young men may yield positive labor market externalities, despite prior work finding weak evidence on contemporaneous wage penalties for young men.

[6] See, for example, Cawley (2004), Han et al. (2009), Gilleskie et al. (2011), Johar and Katayama (2012), and Guardado and Ziebarth (2018).

[7] This is consistent with a "beauty effect" hypothesis in Hamermesh and Biddle (1994).

[8] See, for example, Courtemanche et al. (2016), Courtemanche and Carden (2009), Salois (2012), Currie et al. (2010), Dunn et al. (2012), Anderson and Matsa (2011), and Dunn (2010).

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

Notes: A total of 1,291 unique individuals yield 29,693 person/year observations.
Source: National Longitudinal Survey of Youth, 1979 cohort.

Table 2
SUMMARY STATISTICS—FULL V. ANALYSIS SAMPLE OF 1979 NLSY

	Analysis 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 ($1000s)	17.81	13.18	14.78	12.50
Income 98 ($1000s)	27.14	26.84	25.52	26.53
# of Kids	0.34	0.71	0.37	0.74

Occupation Class Percentages, 1981

Variable	Analysis Sample	Full Sample
No work	45.53	51.14
Professionals	5.70	5.31
Sales & admin	16.35	14.76
Craftsmen	5.01	4.84
Laborers	13.06	11.60
Service	14.35	12.35
N	1,291	3,720

2. DATA

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 come 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 Council for Community and Economic Research (C2ER). County level data on grocery stores, limited service restaurants (fast food), and fitness centers come from Census' County Business Patterns.

The NLSY '79, conducted by the Bureau of Labor Statistics (2013), follows a nationally representative cohort of youths initially aged 14–22 annually from 1979 to 1994 and biennially to 2010.[9] Respondents were asked questions regarding family background, schooling, occupation, hours of work, wages, 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 who missed an interview in the biennial phase were dropped.[10] Table 1 details the sample construction. The final sample consists of 39,211 person-year observations. Table 2 contains descriptive statistics for the full sample of white males and the estimation sample.

[9] http://www.nlsinfo.org.
[10] See Online Appendix B for a brief discussion on sample selection.

TABLE 3

OCCUPATIONAL SORTING—PROPORTIONS OF OBESE AND NONOBESE 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

Individuals' reported occupations are classified into one of five major categories from the 1970 Census Occupational Classification System.[11] Table 3 lists the five occupation categories used in this research and displays the proportion of obese and nonobese individuals selecting into these occupations for three time periods.

2.1. *Dictionary of Occupational Titles and O*NET.* The model includes one measure each for the physical, mental, and social intensity of each occupation for every year in the sample period. These measures of "job requirements" are included in the wage expression as a way to capture some aspect of how body weight affects productivity and also in the nonmonetary part of the utility function. Data from the DOT and O*NET were used to construct these indices of job requirements. The DOT data come from the 1977 edition and updates in 1982, 1986, and 1991. In the mid-1990s, the DOT was 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 and 1,000 "job families." The O*NET focuses on white-collar and service occupations and contains much finer numerical ratings (on level and importance) for far more requirements per occupation than DOT.[12]

2.2. *C2ER Data on Food Prices and the Food Environment.* Food price ratios were constructed using data from C2ER.[13] 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, two-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.[14] Additional data on construction of food price ratios and geographic matching are available in Online Appendix D. From the U.S. Census Bureau's County Business Patterns, I construct grocery stores, limited service restaurants (fast food), and fitness centers per capita in the individual's county of residence over the sample period.

[11] 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.

[12] Online Appendix D contains additional details on forming the requirement indices and crosswalking DOT and O*NET ratings.

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

[14] Utilizing ratios instead of 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.

FIGURE 1

REAL MEAN WAGE BY AGE AND OBESITY STATUS

3. MOTIVATION

Four stylized facts from the NLSY '79 motivate the dynamic stochastic occupational choice model.[15] First, Figure 1 depicts the mean real wage by age and obesity status in the NLSY '79, showing a growing disparity in mean wages between obese and nonobese workers over the life cycle. Although prior work has found mixed results regarding contemporaneous wage penalties for obesity for men, a more recent literature has found stronger effects of adolescent obesity on adult earnings.[16] However, prior work cannot explain the growing disparity in mean wages or yield insight on the mechanisms behind that growth. Second, the growth in observed wage disparity is not observed in all occupations, but concentrated in two of the five occupational categories considered, that is, professional, technical, and managerial (PTM) occupations and sales, clerical, and administrative (SCA) occupations.[17,18,19] 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 that when individuals are obese, they face lower wages but only in "white-collar" occupations.[20] Additionally, returns to own and cross-occupational experience vary by occupation. Experience in the five categories is not rewarded equally.

[15] See Online Appendix A for more detail on the joint implications of these facts and more discussion on the joint estimation of wages and occupational choice, modeling the forward looking individual's optimization problem and the benefits of imposing some structure on the model.

[16] See, for example, Han et al. (2011), Lundborg et al. (2014), and Pinkston (2015).

[17] See Figure 5.

[18] Hamermesh and Biddle (1994) claim that if discrimination explains a wage differential, then wage differences should be observed across occupations.

[19] Although previous work including Han et al. (2009) has documented that weight-related wage differences are magnified in social requirements, static methods cannot explain the growth in the difference in wages.

[20] A regression that pools the five occupational categories yields a negative, but statistically insignificant result as is customary in the literature.

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

Third, given the observed wage differences in Figure 5, below, one would expect that obese workers would choose professional and sales/administrative occupations at a lower frequency than nonobese workers. Figure 4, below, shows this to be the case, but also suggests that wages alone do not explain the differences in choice frequencies.[21] The magnitude of the difference in white-collar occupational choice frequencies between obese and nonobese workers is largest when the sample is aged 24–30, or when wage differences are smallest. As the sample ages, the weight-based wage differences grow, but the difference in occupational choice frequencies between obese and nonobese workers shrinks. This is counterintuitive, unless labor demand frictions or worker preferences are influencing the employment decisions of individuals of different body weights.[22] The obese and nonobese also differ in their occupational transition patterns. Section 6 summarizes these differences.

Finally, occupational choice frequencies vary not just by contemporaneous body weight, but by future body weight. Figure 2 depicts the occupational choice frequencies of workers of currently healthy body weight for the years 1981–1984.[23] Figure 2 shows that conditional on currently healthy body weight, workers who will be obese at some point during the sample are less likely to sort into the white-collar occupations that have higher expected wages and returns to experience, but lower wages for workers with higher body weight. Although prior work on body weight and labor market outcomes has at least touched on each of these aspects, we cannot examine how the dynamics of expected future wage penalties, switching costs, job requirements, and worker preferences interact to generate the jointly observed wage and occupational choice outcomes without imposing some structure on the model.

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 nonmonetary costs of each alternative. Subsections 4.1–4.4 define the components of contemporaneous utility from each alternative, the distribution of wages and growth of human capital, and the weight transition

[21] The propensity for heaver workers to choose blue-collar work has been documented in Pagan and Davila (1997), Kelly et al. (2014), and Han et al. (2011).

[22] Although prior work has described the observed differences in occupational choice frequencies between workers of different body weights, it has not modeled the individual's occupational choice.

[23] The cohort is aged 19–25 during this period.

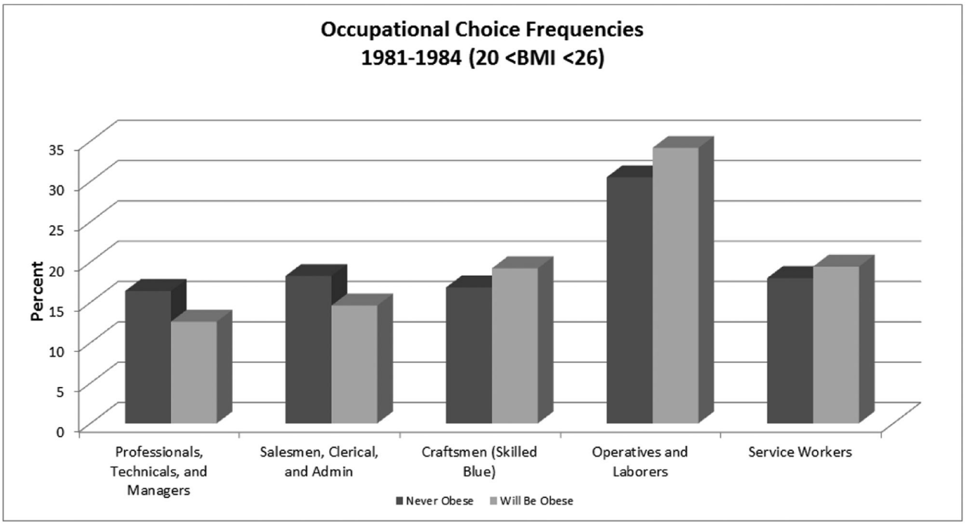


FIGURE 2

EARLY CAREER OCCUPATIONAL CHOICES BY FUTURE OBESITY STATUS

expression. Subsection 4.5 formulates the individual's dynamic optimization problem in a value function framework.

An individual jointly decides whether to work, how much to work, in which occupation to work, and whether to attend school. There are a total of 23 alternatives, indexed hj, available in each period. The employment alternatives, h, are:[24]

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

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

$$
\begin{array}{ll}
j=0: & \text{No occupation}, \\
j=1: & \text{Professionals, technicals, managers}, \\
j=2: & \text{Salesmen, clerks, administrative workers}, \\
j=3: & \text{Craftsmen}, \\
j=4: & \text{Operatives and laborers}, \\
j=5: & \text{Service workers.}
\end{array} \tag{2}
$$

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.[25,26] Agents

[24] Working less than 15 hours is treated as "not working."

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

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

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 or part time or attend school part-time in conjunction with working part-time.[27] Degree attainment is determined by years of schooling only, instead of modeled as a separate decision.

The state vector $\mathbf{S_t}$ includes age, spousal earnings, number of children, years of schooling, body mass, years of experience in each of the five occupational categories, and the occupation chosen in the previous period. Known to the agent, but not the econometrician, are time-invariant unobserved "type" 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 1 for all alternatives. The employment decision in period t fully determines the values of the experience and education state variables at the end of the period. Body mass, marital status, and number of kids are probabilistically affected by the individual's employment decision.

4.1. *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, switching costs of changing occupational categories between periods, and unobserved heterogeneous type, ϕ. In the function below, c_t represents consumption, and $h_t(\mathbf{d}_t)$ defines the number of hours worked and/or spent in school for the set of alternatives. The $M_j(\cdot)$ term contains the annual fixed costs of participating in occupation j, including any switching costs incurred if the individual chose occupation $j' \neq j$ in the preceding period. $M_s(\cdot)$ contains any costs of schooling in alternative hj. $N(h_t(\cdot))$ represents the variable costs of working h_t hours. The preference error term in the utility function, ϵ_t^{hj}, is assumed to be a generalized extreme value (GEV) error term nested at the occupation level to allow for correlation in the preference shocks for alternatives within each occupation.[28] Per-period utility for each alternative is expressed as

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

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.[29] The budget and time constraints are

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

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 $I(\mathbf{S}_t)$ denotes unearned spousal income, and Ω represents the individual's total amount of time in a given period.

4.2. *Nonmonetary Costs: Fixed, Switching, and Variable.* Individuals are assumed to receive wage offers from every occupational sector in each period. However, individuals in the data do

[27] Details on special cases and construction of completed years of schooling can be found in Online Appendix D.1.

[28] Note that all terms in Equation (3) are conditional on unobserved "type," ϕ. The specifics on how unobserved heterogeneity enters the model are discussed in Subsections 4.2–4.4 and 5.2.

[29] Time spent on education counts as "nonleisure" 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. If an agent pursues a part-time work, part-time school combination, his total nonleisure time is the sum of his hours spent working plus the 20 hours per week for part-time schooling.

not always select into occupations with the frequency one would expect in the absence of labor demand frictions if individuals were pure wealth maximizers. To reconcile these differences, the model includes three nonmonetary costs for each employment alternative. First, the model includes per-period fixed costs of participating in each occupation that depend on human capital, body mass, and job requirements. Per-period fixed costs are incurred when an individual works in a given occupation, regardless of the number of hours worked. Grouped with the fixed costs are switching costs incurred when an individual transitions into occupation j from another occupation, j'. Switching costs vary by body mass, age, and previous occupation. Third, the model includes variable costs of working additional hours to examine how the marginal costs of working vary by body weight and job requirement.

Per-period fixed costs are a function of age, education, body weight, and the requirements of the occupation, as shown in Equation (5).[30] 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 physical, mental, and social requirements of that occupation are denoted by $\mathbf{J}_{jt} = [J^p_{jt}, J^m_{jt}, J^s_{jt}]$, respectively.[31] The ϕ term captures unobserved heterogeneity in the fixed costs individuals face for each occupation, and ρ^J_j captures the magnitude of the importance of that unobserved heterogeneity.[32] Body mass, B_t, is modeled as an individual's distance from a "healthy weight."[33] Occupational requirements are interacted with age and B_t. The nonmonetary costs of an occupational alternative include additional costs when the individual was not employed in that occupation in the preceding period. These "switching costs" (detailed in the second line of Equation (5)) vary by the occupation from which the individual transitions, age (a_t), and body weight. The per-period fixed and switching costs of participating in an occupation j are expressed as

$$(5)\qquad \begin{aligned} M_j(\mathbf{S_t}|\phi) &= \alpha \mathbf{J}_{jt} + \alpha \mathbf{J}_{jt} a_t + \alpha \mathbf{J}_{jt} B_t + \alpha^j_0 + \alpha^j_1 a_t + \alpha^j_2 \mathbf{E}_t + \alpha^j_5 B_t \\ &\quad + \sum_{j' \neq j} \alpha^j_{6+j'} \mathbf{1}(d^{hj'}_{t-1} = 1) + \alpha^j_{11} \mathbf{1}(d^{hj}_{t-1} \neq 1) B_t + \alpha^j_{12} \mathbf{1}(d^{hj}_{t-1} \neq 1) a_t + \rho^J_j \phi. \end{aligned}$$

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.

$$(6)\quad M_s(\mathbf{S_t}|\phi) = \alpha^s_0 \mathbf{E}_t + \alpha^s_1 \left(\prod_{h=4}^{6} \mathbf{1}\left(d^{hj}_{t-1} \neq 1\right) \right) + \alpha^s_2 a_t + \alpha^s_3 a_t^2 + \alpha^s_4 a_t \left(\prod_{h=4}^{6} \mathbf{1}\left(d^{hj}_{t-1} \neq 1\right) \right) + \rho^S \phi.$$

The individual also incurs variable costs of working or attending school more than the minimum threshold of 15 hours. Equation (7) shows the expression for the variable costs of an employment alternative. The same variables that determine per-period fixed costs determine variable costs, but are interacted with h_t. A ϕ term and a factor loading, ρ^N, is included to capture heterogeneity in preferences for working additional hours, thereby allowing for correlations between propensity to choose certain occupations and propensity to work more/fewer hours. In this expression, m_t denotes marital status and k_t represents the individual's number of children. The occupational requirements $\mathbf{J}_{jt}$ and the interaction of those requirements with body weight

[30] The term "fixed costs" is used to imply that these costs do not vary by the number of hours worked in a particular occupation.

[31] Because the levels of job requirements vary across occupations, the coefficients on the variables for job requirements are held fixed across occupations. Details of the construction of these indices are available in Online Appendix D.5.

[32] See Section 5.2 for more details.

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

also affect the cost of working more hours: [34]

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

Body weight therefore affects both the per-period fixed and variable costs of each occupation via the requirements of the job, but also has occupation-specific effects on per-period fixed and switching costs.[35]

4.3. *Distribution of Wages.* The distribution of wages, not only the conditional mean, is meaningful in solving the model and estimating parameters.[36] Instead of imposing a parametric distribution on wages, I estimate the full density of wages inside the model using CDE. Defining the density of wages:

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

where the conditional density of wages is determined by the state vector $\mathbf{S_t}$ (includes work experience, education, and body weight), occupational requirements, and occupation-specific unobserved heterogeneity, ϕ. Body mass and the vector of job requirements are interacted to capture the role of "productivity" in body-weight-specific wage differences.[37] Differences in occupational experience and education are directly controlled for. Returns to education and experience are allowed to vary by body weight. The coefficients on body weight alone capture the residual effect of body weight on wages, conditional on experience and education.[38]

4.3.1. *Evolution of experience and education.* The model allows work experience to accumulate faster for agents who choose to work more hours. The state variable x_t^j denotes full-time years of experience in occupation j entering time t. Work experience in each occupation transitions as follows:

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

[34] 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 55 hours for overtime work. For alternatives that are observed in the data, I use the observed value of h_t to calculate $N(h_t(\mathbf{d}_t), \mathbf{S_t})$.

[35] The expression for the "variable" costs includes both the forgone costs of leisure time as well as the differences in the nonmonetary costs of working additional hours by occupation and worker characteristic. However, the baseline cost of forgone leisure time alone is captured by ψ_1.

[36] 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).

[37] To the extent that job requirements affect body weight, any compensating differentials are implicitly included in the effects of job requirements on wages. A supplementary simulation in Online Appendix E explores the extent to which individuals incorporate the effects of employment decisions on future body weight into their decisions.

[38] Estimation of the distribution of wages by CDE is discussed in greater detail in Subsection 5.1.

Years of schooling accrue as follows:

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

4.4. *Weight Transition.* The model permits employment decisions to affect body weight. Body weight evolves conditional on previous body weight, food prices, food supply factors, environmental factors, wages, family states, the requirements of the occupation selected in that period, and hours worked. The state transition probabilities for body mass are estimated using CDE, which permits marginal effects to vary over the support of the distribution of the dependent variable.[39] Conditional on body mass B_t in period t, the density of B_{t+1} is

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

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

The individual's employment decision can have both direct and indirect effects on body weight. Direct effects come through amount of on-job physical activity and number of hours worked. Food consumption and exercise behavior held constant, lower on-job activity levels equate to lower caloric expenditure. Indirect effects would occur as an individual's employment decision affects his off-work decisions regarding food and exercise, which then affects body weight. The effects of job requirements on body weight are likely a function of both direct and indirect effects.[40] Primarily due to data limitations, I do not model individuals' food and exercise decisions.[41] Estimated parameters in the weight transition expression should not be interpreted as structural parameters, as I cannot isolate direct and indirect effects.

4.5. *Optimization Problem.* The individual's objective is to choose the alternative at time t that maximizes expected lifetime utility. Lifetime utility at time t is represented using a Bellman formulation composed 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 a GEV preference shock:

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

The alternative specific lifetime value of state $\mathbf{S}_t$, conditional on unobserved "type" ϕ, is

$$V_{hj}\left(\mathbf{S}_t, \epsilon_t^{hj} | \phi\right) = \overline{U}_{hj}(\mathbf{S}_t, \phi) + \epsilon_t^{hj} + \beta \int_B f\left(B_{t+1} | B_t, \mathbf{d}_t, \mathbf{S}_t, \mathbf{J}_{jt}, X_t^G, \phi\right) \tag{13}$$

$$\sum_{k=0}^{1} \sum_{m=0}^{3} P[M_{t+1} = m | \mathbf{S_t}, \mathbf{d_t}] P[K_{t+1} = k | \mathbf{S_t}, \mathbf{d_t}] E[V(\mathbf{S}_{t+1} | \phi) | d_t^{hj} = 1] dB,$$

[39] Details are discussed in the next section.

[40] Additional discussions of the implications of unmodeled food/exercise choices, including a brief discussion about possibly spurious relationships, are in Online Appendix B.1.

[41] 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% of total daily calorie expenditure is due to discretionary exercise, thereby reemphasizing the importance of on-job activity.

where $V(\mathbf{S}_{t+1}|\phi)$ is the maximal expected lifetime utility of being in state $\mathbf{S}_{t+1}$.[42] The value function is conditional on the unobserved heterogeneity component ϕ. Expectations are taken over the future wage and preference shocks. I integrate over the estimated conditional density of wages to calculate expected values in solving the model. Let $\overline{V}_{hj}(\cdot) = V_{hj}(\cdot) - \epsilon_t^{hj}$. Assuming that ϵ_t^{hj} follows a generalized extreme value distribution nested at the occupation level, then maximal expected lifetime utility has the following closed-form expression:

$$V(\mathbf{S}_{t+1}|\phi) = \gamma + ln\left(\sum_{k=0}^{5}\left(\sum_{hj\in k} exp\,(\overline{V}_{hj}(\mathbf{S}_{t+1}|\phi))^{\lambda_k}\right)\right), \forall t, \tag{14}$$

where γ is Euler's constant and λ_k is the coefficient that determines the strength of the correlation in the errors between alternatives in occupation k. Furthermore, because the error term ϵ_t^{hj} is additively separable, the conditional choice probabilities take the following form:

$$p\left(d_t^{hj} = 1|\mathbf{S}_t, \phi\right) = \frac{\left(\sum_{hj\in j} \exp(\overline{V}_{hj}(\mathbf{S}_{t+1}|\phi)\right)^{\lambda_j - 1}\exp(\overline{V}_{hj}(\mathbf{S}_t|\phi)}{\sum_{k=0}^{5}\left(\sum_{hj\in k} \exp(\overline{V}_{hj}(\mathbf{S}_{t+1}|\phi)\right)^{\lambda_k}}. \tag{15}$$

The likelihood function consists of these choice probabilities, augmented to take expectations over unobserved wages as in Stinebrickner (2001), transition probabilities for marriage, body mass, and number of children.[43]

5. EMPIRICAL IMPLEMENTATION

5.1. *Conditional Density Estimation.* 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 to form the sequences are logit probabilities.

CDE also permits the marginal effects of explanatory variables to vary over the support of the dependent variable.[44] In the weight transition expression, we can similarly evaluate how the marginal effect of on-job physical activity varies over the support of body weight. Gilleskie and Mroz (2004) show that expected wages can be approximated using the estimated density:

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

where $\lambda(k, X)$ 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

[42] 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 Online Appendix C.

[43] Details on initial conditions and construction of the likelihood function are available in Online Appendix C.

[44] As 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 vary over the distribution of wages, flexible marginal effects are a compelling feature of CDE in this context.

estimated approximation instead of integrating over a continuously distributed error term. The expectations and transition probabilities for body mass are similarly calculated.[45]

5.2. *Permanent Unobserved Heterogeneity.* Addressing unobserved heterogeneity is critical for two reasons. First, there may be correlations between the factors outside the model that influence weight gain, employment decisions, and wages. For example, if the kinds of individuals who like to eat also like to work with their hands, failing to address this heterogeneity will lead to biased estimates. Second, incorporating unobserved heterogeneity also provides a way to address the independence of irrelevant alternatives problems associated with extreme value errors, particularly between classes of occupations. For example, certain individuals may be more likely to be observed in professional/managerial occupations and sales/administrative occupations than other occupations. Although the nested logit structure of the error term permits correlation in the shocks within occupations, allowing for correlations in the unobservable errors will capture some correlation in individuals' propensity to be observed in "white-collar" or "blue-collar occupations" as well as unobservable correlations between the factors that affect wages and the nonmonetary costs of each alternatives.

To that end, 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 expression, and preference for working additional hours. Note that all expressions to this point have been conditional on unobserved type ϕ. Permanent unobserved heterogeneity enters the model through the ϕ terms, each of which is interacted with a factor loadings (ρ). The factor loadings allow for a different effect of the unobserved $\phi \in [0, 1]$ in each expression. Instead of imposing 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).[46] The model therefore allows for correlations in the unobserved tendency to earn more/less in each occupation, tendency to gain weight, fixed costs for each occupation, preference for school, and preference for working fewer hours.

5.3. *Identification.* The econometric identification of this model comes through three sources: exclusion restrictions, the assumed timing and structure of the model, and nonlinearities in the model. I assume that the individual's body weight is realized and known at the time the individual realizes his or her wage draws and makes his or her choice of employment. The expression for body weight transition contains several arguments that are excluded from the expressions for wages and nonmonetary costs of each occupation: price ratios of fast food to produce and processed foods to produce, and fast-food restaurants, grocery stores, and fitness centers per capita in the county where the individual resides. To appeal to timing restrictions, I must estimate endogenous initial conditions for body weight and education. 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 from the weight equation. Although the model is estimated jointly using full-information maximum likelihood, there is clearly reason to believe that the errors in the expressions for wage and nonmonetary costs are not independent. I rely on the discrete factor random effects to absorb the correlations in the error terms.

Additionally, I make several normalizations to identify the scale of the parameters. The utility of not working is normalized to zero. The switching costs of transitioning to unemployment are

[45] K and L are the number of quantiles into which the data for wages and weight are divided. Here, 20 was used for L and 25 for K. See Gilleskie and Mroz (2004) for a discussion on choosing the optimal number of cells.

[46] The discrete factor random effects method performs well in approximating both normal and nonnormal distributions (Mroz, 1999).

TABLE 5
MARGINAL EFFECTS OF JOB REQUIREMENTS AND BMI ON WAGES: OCCUPATION-INVARIANT EFFECTS

Requirement	Quartile	Effect	Requirement *BMI	Quartile	Effect
Physical	Lower	1.10	Physical	Lower	0.03
	Inter	2.97		Inter	0.18
	Upper	3.48		Upper	0.40
Mental	Lower	−0.09	Mental	Lower	−0.01
	Inter	0.11		Inter	−0.05
	Upper	0.48		Upper	−0.05
Social	Lower	−0.37	Social	Lower	−0.04
	Inter	0.22		Inter	−0.05
	Upper	1.15		Upper	−0.12

NOTES: Values are in 2015 dollars.

normalized to zero, as is the vector of job requirements when not working. The uniqueness of the parameters in the expressions for fixed costs, variable costs, and switching costs are all identified from differences in observed choice frequencies, conditional on observed wages and the values in the individual's state vector.[47] The exponent in the Constant Relative Risk Aversion (CRRA) utility function is econometrically identified through choice frequencies of full, part, or overtime alternatives as unearned spousal income changes.[48]

6. RESULTS

6.1. *Wages.* Although CDE has several benefits, hazard parameter estimates are not directly interpretable as marginal effects. Marginal effects are calculated by first taking 10,000 draws from the empirical state space of education and experience with BMI fixed at the sample mean. A draw is then taken from the wage distribution for each value of the state space and BMI. The mean wage is then calculated for three segments: draws below the observed 25th percentile of the wage percentile, wages above the observed 75th percentile of the raw data, and draws from the interquartile range. I then increase education, experience, or requirement by one unit, holding all other state variables constant, and again calculate the mean for each segment of the distribution of wages. I compare the two means for the marginal effect. The interaction effects with BMI are calculated by increasing both the state/variable requirement and BMI by one unit and comparing the difference in means to the case where the only state/requirement variable was increased. 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.[49]

The right column in Table 5 shows that higher body weight leads to lower wages in mentally and socially intensive occupations.[50] This result that is consistent with previous work has also found that higher body weight leads to lower wages in socially intensive jobs (Hamermesh and

[47] See Online Appendix B.2 for additional context.

[48] Spousal income is discretized into four states: not married and earnings by tercile. Spousal income evolves stochastically and is influenced by individuals' choices, but individuals do not directly choose their spouse's income. Specifically, individuals' wages do affect the probability that their spouse will earn more or less in the next period (see Online Appendix C.3 for additional information.). So, although I treat spousal income as exogenous in the sense that I do not model the joint household labor supply decision, individuals' wage in period t affects the probability their spouse is a low, middle, or high earner in period $t+1$. The extent to which spousal income affects the full-, part-, or overtime decision conditional on wages informs us about the curvature of the utility function with respect to consumption. The pursuit of education early in the model also aids in the identification of the CRRA parameter. If the CRRA coefficient α is relatively large, marginal utility from consumption decreases rapidly. Therefore, individuals will value the increased expected present discounted future earnings resulting from education less than they would if α is close to zero.

[49] Tables 13 and 14 in Online Appendix C.4 contain parameter results from the CDE of wages and a discussion about how to interpret these hazard function parameters.

[50] B_t is the distance between an individual's BMI and the "healthy weight" boundary of 25.

TABLE 6
OCCUPATION-SPECIFIC MARGINAL EFFECTS—BMI AND INTERACTIONS

Variable	Quartile	Professional Estimate	Sales/Admin Estimate	Craftsmen Estimate	Laborers Estimate	Service Estimate
BMI	Lower	−0.11	−0.01	0.20	0.11	0.13
	Inter	−0.14	−0.07	0.02	−0.08	−0.12
	Upper	−0.28	−0.08	−0.27	−0.10	−0.29
BMI ×	Lower	−0.05	0.00	0.06	−0.03	0.10
Education	Inter	−0.04	−0.07	0.09	0.12	0.12
(Year)	Upper	−0.07	−0.11	0.07	0.08	0.09
BMI ×	Lower	−0.49	−0.12	0.00	0.33	−0.18
Bachelor's Degree	Inter	−0.55	−0.40	−0.25	0.31	−0.05
	Upper	−0.57	−0.51	−0.16	−0.41	0.04
BMI ×	Lower	−0.01	0.11	0.02	−0.04	−0.11
Professional	Inter	−0.03	−0.03	−0.02	−0.12	−0.06
Experience	Upper	−0.08	−0.12	−0.04	−0.15	0.06
BMI ×	Lower	0.01	0.07	0.06	−0.06	−0.07
Sales/Admin	Inter	−0.04	−0.06	0.00	−0.04	−0.02
Experience	Upper	−0.07	−0.14	−0.03	−0.03	−0.02
BMI ×	Lower	0.01	0.06	0.02	0.02	0.02
Craftsmen	Inter	−0.06	0.11	0.01	0.02	0.07
Experience	Upper	−0.04	0.01	0.01	0.02	0.12
BMI ×	Lower	0.01	0.03	0.01	0.01	0.01
Laborer	Inter	0.03	−0.02	0.02	0.01	0.01
Experience	Upper	−0.02	0.02	0.03	0.00	0.02
BMI ×	Lower	0.03	0.03	0.02	0.00	0.05
Service	Inter	0.05	−0.14	−0.07	−0.03	0.01
Experience	Upper	0.03	−0.19	−0.05	−0.07	−0.05

NOTES: Values are in 2015 dollars.

Biddle, 1994; Han et al., 2009; Johar and Katayama, 2012). The relationship between body mass and wages in physically intensive occupations is positive, which is not surprising, given that the primary physical aspect of the job is strength. 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.

Table 6 contains the occupation-specific marginal effects of body weight on wages. Conditional on job requirements, higher body weight is linked to lower wages in PTM occupations and to a very limited extent sales and administrative occupations. The largest effects are again found in the upper quartile of the wage distribution.[51] Higher body mass is also linked to lower returns to "white-collar" (encompassing PTM occupations and sales and administrative occupations) experience in nearly all occupations. Additionally, higher body mass reduces returns to education in white-collar occupations. The effects of weight on wages are most pronounced in the top quartile. The variation in returns to higher education, wage differences for social requirements, and variation in returns to experience, all pronounced in the top quartile of the wage distribution, contribute to the observed growing wage gap between obese and nonobese workers over the sample period. Consistent with prior work on how BMI affects wages of white men, estimated effects of obesity alone on wages are a small share of the wage gap.[52]

[51] 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.

[52] For example, in professional occupations among individuals in the upper quartile of the wage distribution, an individual with a BMI of 31 (obese) is estimated to make \$0.56 per hour less than an individual with a BMI of 29 (nonobese). That difference, compared to the mean of the upper quartile of the wage distribution, amounts to a less than 1% difference.

TABLE 7
UTILITY FUNCTION PARAMETERS

Variable	Estimate	ASE
α	0.6032	0.098

Parameters from Equation (7) Occupation-Invariant Variable Costs			Parameters from Equation (6) Fixed Costs of Schooling		
Variable	Estimate	ASE	Variable	Estimate	ASE
Constant	−0.437	0.037	Constant	−4.995	0.112
M_t	−0.215	0.026	(Ed $\geq$ 12)	3.731	0.087
K_t	−0.078	0.012	(Ed $\geq$ 16)	4.805	0.075
B_t	0.119	0.014	t	0.173	0.062
hours*B_t	0.007	0.011	t^2	−0.056	0.038
Physical	−0.324	0.078	Working	3.985	0.092
Mental	−0.607	0.083	Returning	0.059	0.009
Social	0.205	0.072			
Physical*B_t	−0.031	0.005			
Mental*B_t	−0.023	0.004			
Social*B_t	0.013	0.005			
t	−0.000	0.011			
hours*t	0.000	0.010			
hours	0.452	0.062			
Unobserved heterogeneity					
Factor loading	−0.528	0.065	Factor loading	0.101	0.010

NOTES: ASE: Asymptotic Standard Error.

6.2. *Nonmonetary Costs.* Tables 7 and 8 report estimated nonmonetary 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 that have greater social requirements. Linking with the wage results, heavier individuals face lower wages and higher fixed costs in socially intensive jobs, whereas the opposite is true for physically intensive jobs. Results also show that greater body mass leads to higher switching costs when entering white-collar jobs, which are also the most socially intensive. The effects are over twice the magnitude in PTM occupations ($6,200 at the mean wage, per 5 BMI points) as SCA jobs ($2,300 per 5 BMI points).

6.3. *Weight Transition.* Marginal effects from the body weight expression are also calculated with simulation. Results for key parameters are shown in Table 9.[53] Conditional on education, income, and age, physically intensive jobs are shown to increase body mass among individuals of low body weight, but slightly decrease body weight among heavier individuals. Mental requirements do not strongly affect body weight. Among the characteristics of the built environment, higher ratios of fast food to produce and processed food to produce both reduce body weight among heavier individuals.

6.4. *Model Fit.* To evaluate how the model reproduces the key-stylized facts of the data, I simulate employment decisions and wages using the model and the estimated parameters for 100,000 individuals. Initial conditions are randomly drawn using observed frequencies in the data and the estimated parameters of the model.[54] Figure 3 shows the predicted proportions of chosen occupations by age and the same proportions from the observed data. Figure 4 plots

[53] In Online Appendix C.4, Table 15 contains the parameter estimates for the body mass transition expression.

[54] Details are available in Online Appendix C. An individual's "type" is also drawn randomly using proportions from the estimated distribution of unobserved heterogeneity.

TABLE 8
UTILITY FUNCTION PARAMETERS (EQUATION (5))—SWITCHING AND PER-PERIOD FIXED COSTS

Occupation Invariant Fixed Costs

Requirement	Estimate	ASE	Requirement × t	Estimate	ASE	Requirement × Body Mass	Estimate	ASE
Physical	0.271	0.050	Physical	−0.000	0.000	Physical	0.017	0.006
Mental	0.041	0.048	Mental	0.003	0.001	Mental	−0.012	0.006
Social	0.068	0.045	Social	−0.001	0.001	Social	0.025	0.005

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	0.580	0.263	0.345	0.126	−1.367	0.323	−1.541	0.451	0.063	0.080
Years of School	−0.162	0.006	−0.040	0.046	−0.002	0.000	0.002	0.000	−0.002	0.002
(Ed $\geq$ 12)	−0.960	0.170	−0.535	0.169	−0.040	0.041	−0.131	0.123	−0.065	0.139
(Ed $\geq$ 16)	−1.631	0.033	−0.526	0.083	−0.525	0.181	0.793	0.108	−0.266	0.268
Body mass	0.056	0.091	0.020	0.006	−0.009	0.002	−0.053	0.108	0.037	0.108
t	0.016	0.019	0.025	0.012	0.012	0.005	0.013	0.007	0.009	0.014

Occupation-Specific Switching Costs

Occupation	Professional		Sales & Admin		Craftsmen		Laborers		Service	
Variable	Estimate	ASE	Estimate	ASE	Estimate	ASE	Estimate	ASE	Estimate	ASE
$\mathbf{1}[j_{t-1} = 0]$	5.012	0.342	4.709	0.361	4.468	0.301	2.222	0.256	2.755	0.331
$\mathbf{1}[j_{t-1} = 1]$	–	–	3.735	0.451	4.790	0.370	2.136	0.442	3.021	0.350
$\mathbf{1}[j_{t-1} = 2]$	3.550	0.372	–	–	4.347	0.098	2.009	0.433	2.304	0.418
$\mathbf{1}[j_{t-1} = 3]$	4.148	0.350	5.020	0.330	–	–	2.010	0.425	1.672	0.385
$\mathbf{1}[j_{t-1} = 4]$	4.725	0.432	3.983	0.378	3.720	0.281	–	–	2.755	0.267
$\mathbf{1}[j_{t-1} = 5]$	4.413	0.325	4.263	0.347	4.746	0.096	2.087	0.360	–	–
$\mathbf{1}[j_{t-1} \neq j] * t$	0.023	0.004	0.100	0.022	0.078	0.021	0.130	0.019	0.098	0.018
$\mathbf{1}[j_{t-1} \neq j] * B_t$	0.058	0.008	0.026	0.006	0.012	0.008	−0.022	0.012	0.009	0.012
Unobserved Heterogeneity										
Factor Loadings	−0.105	0.090	2.492	0.149	−1.786	0.839	−0.828	0.093	1.753	0.194
Nesting Parameter (λ_j)	0.603	0.010	0.362	0.008	0.330	0.007	0.411	0.008	0.468	0.012

NOTES: Point estimates are normalized to estimated scale parameter of error term $\tau = 5.0115$.

the observed and predicted proportions of occupations chosen for the obese and nonobese by specific age groups. The model predicts the relative differences between the obese and nonobese well. In each age group in the data, obese workers are less likely to be found in professional occupations than nonobese workers.

Figure 5 plots the observed and predicted wages for the obese and nonobese by age for each occupational category. The model predicts the observed growth in wage disparity on the basis of weight in both "white-collar" occupations.[55,56] Table 10 contains the observed and predicted transition matrices for obese and nonobese individuals. Although the model matches some transition frequencies relatively well, some of these predictions are substantially off. For example, among both nonobese and obese individuals, the model overpredicts substitution

[55] In the observed data from professional occupations, obese workers make \$2.06 per hour (in 2015 dollars) less than their nonobese counterparts at age 25, and \$10.25 less than nonobese workers at age 45. The model predicts these differences to be \$2.69 and \$11.23 at ages 25 and 45, respectively. The model also predicts the growth in the difference in mean wages as individuals age for SCA occupations. In the data, obese workers earn \$3.41 per hour less than their nonobese counterparts at age 25, and \$8.90 less at age 45. The model predicts these differences to be \$2.56 and \$7.90, respectively.

[56] Note that the scaling is smaller in the bottom three panels of Figure 5, as mean wages in these occupations were lower in both initial values and growth rates over the sample period.

TABLE 9

MARGINAL EFFECTS OF KEY VARIABLES ON BODY MASS INDEX

Work-Related Variable	Quartile	Effect	Geographic Variable	Quartile	Effect
Physical Requirement	Lower	0.14	Proc. Food Price Ratio	Lower	0.25
	Inter	0.04		Inter	0.10
	Upper	−0.02		Upper	−0.10
Mental Requirement	Lower	0.00	Fast Food Price Ratio	Lower	−0.05
	Inter	0.00		Inter	−0.05
	Upper	0.02		Upper	−0.04
Hours	Lower	−0.03	Fast Food Per Capita	Lower	−0.28
	Inter	0.01		Inter	−0.02
	Upper	−0.04		Upper	0.24
Wage	Lower	−0.04	Grocery Per Capita	Lower	1.10
	Inter	0.01		Inter	0.15
	Upper	0.04		Upper	−1.15
			Fitness Centers Per Capita	Lower	1.55
				Inter	0.21
				Upper	−1.51

NOTES: Values are in BMI points.

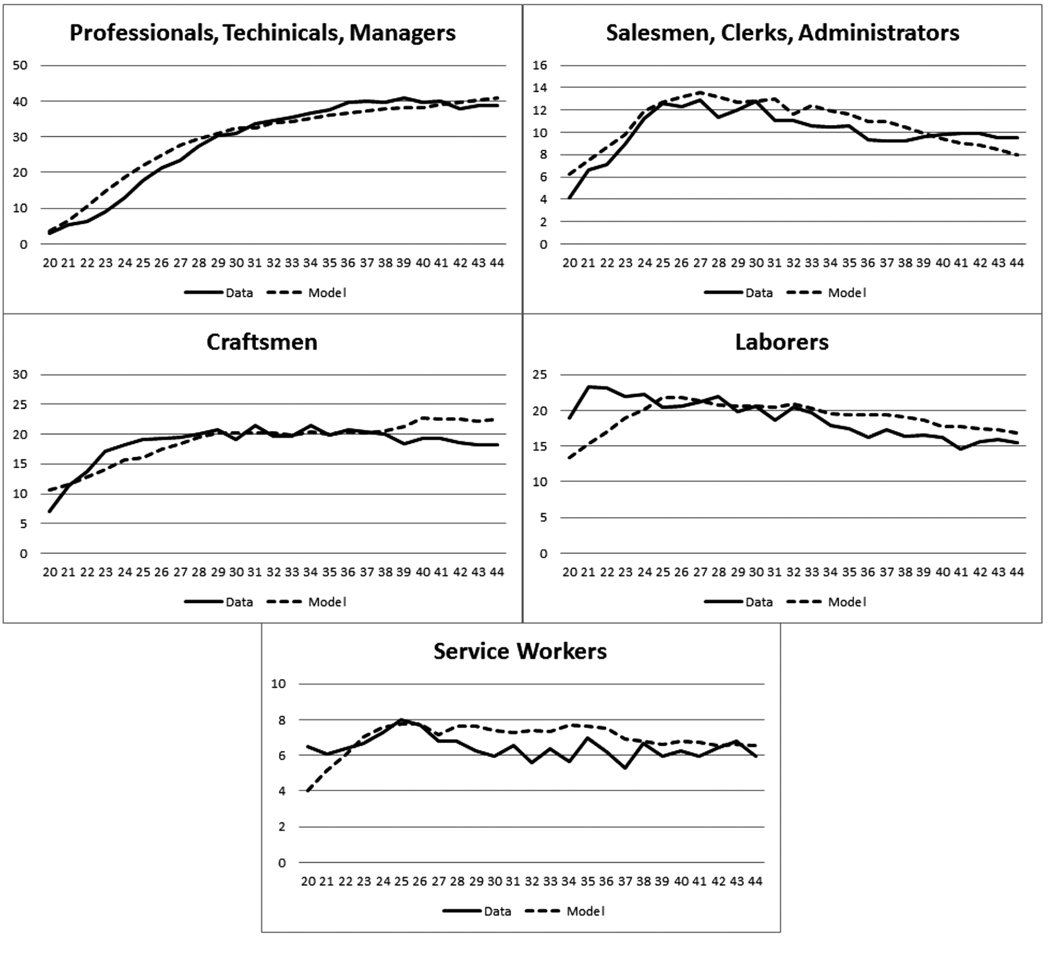


FIGURE 3

PERCENTAGE OF INDIVIDUALS CHOOSING EACH OCCUPATION BY AGE, MODEL V. DATA

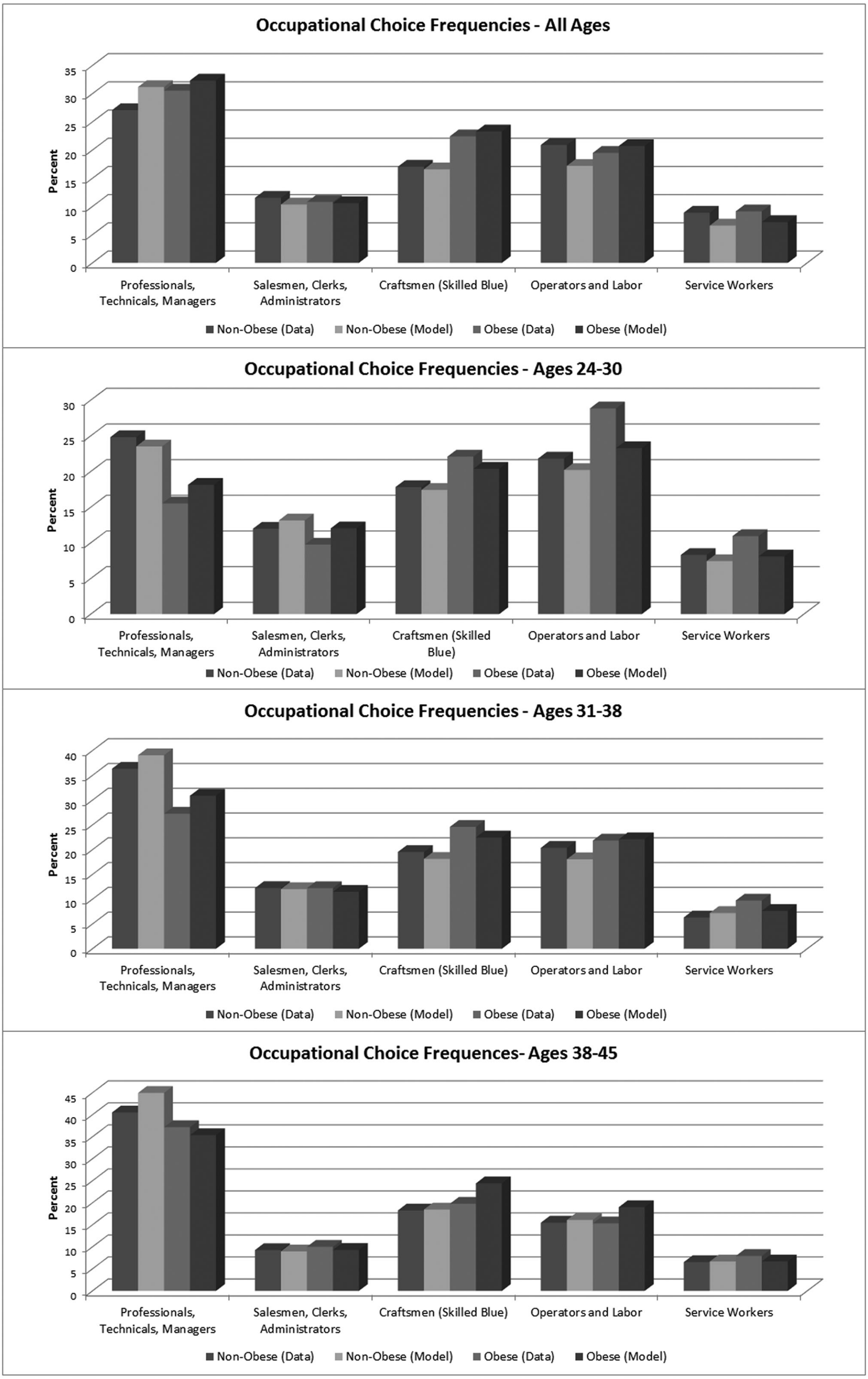


FIGURE 4

PREDICTED AND OBSERVED PROPORTIONS OF OCC'S, OBESE AND NONOBESE

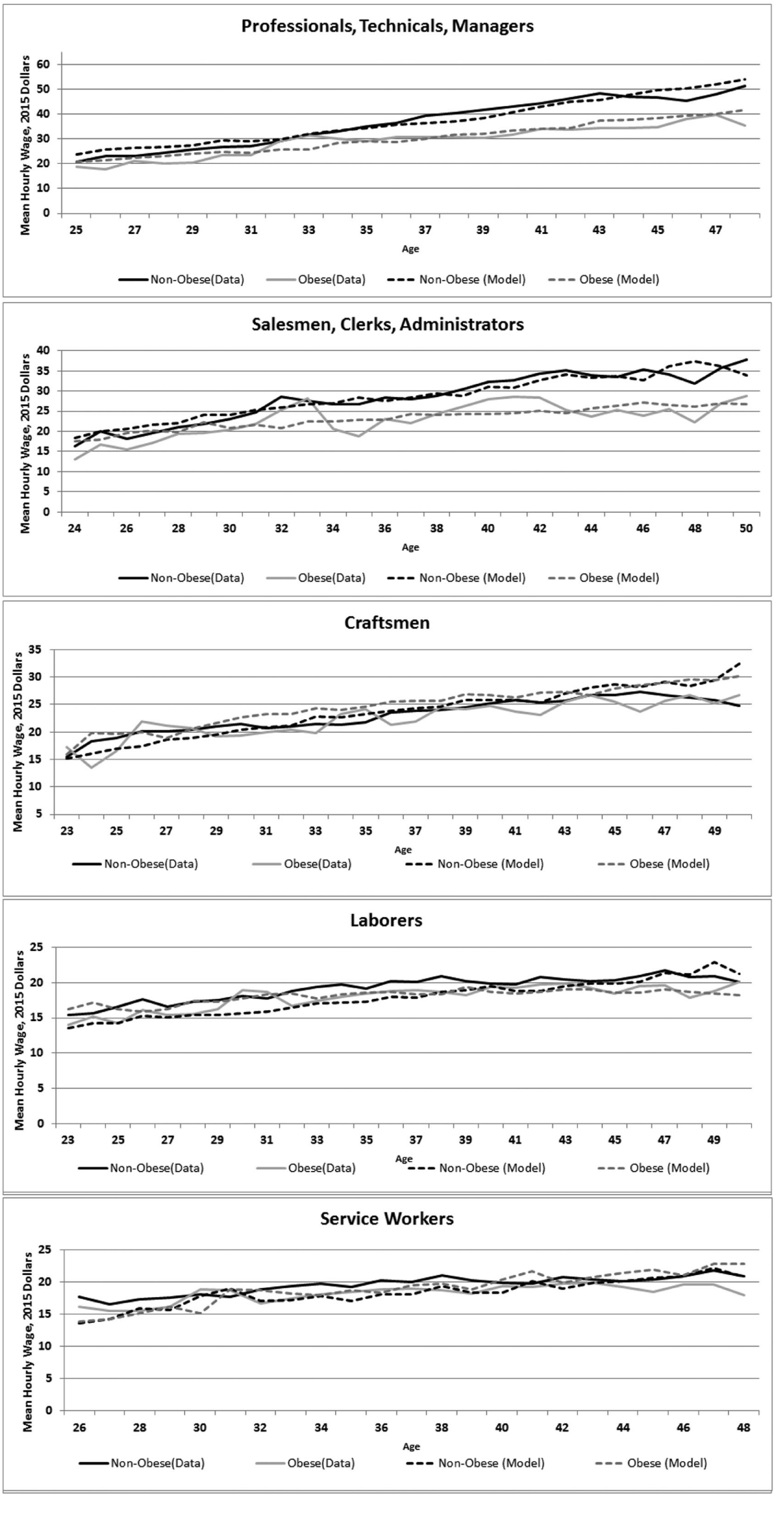


FIGURE 5

PREDICTED AND OBSERVED DIFFERENCES IN WAGES BETWEEN THE OBESE AND NONOBESE

Table 10
OCCUPATIONAL TRANSITIONAL MATRIX

	Nonobese Individuals: $t-1$ in Rows, t in Columns						
	No Work	Prof/Mgr	Sales/Admin	Craftsmen	Ops/Labor	Service	Total
No Work	69.55	8.81	4.11	5.22	8.58	3.72	100.00
(Model)	66.35	6.05	5.08	7.51	10.63	4.37	100.00
Prof/Mgr	4.56	83.27	4.63	3.78	2.31	1.46	100.00
(Model)	1.37	85.77	3.60	3.62	4.21	1.42	100.00
Sales Admin	5.29	16.84	65.78	3.30	7.31	1.48	100.00
(Model)	9.53	14.12	57.08	7.37	9.52	2.39	100.00
Craftsmen	4.14	7.27	1.90	72.95	12.26	1.39	100.00
(Model)	8.88	7.98	4.08	65.73	9.01	4.33	100.00
Ops/Labor	6.14	4.42	4.49	12.75	68.90	3.29	100.00
(Model)	11.69	6.99	6.37	10.13	58.23	6.59	100.00
Service	8.66	7.59	2.83	5.61	10.69	64.62	100.00
(Model)	16.48	12.80	6.11	7.05	10.64	46.92	100.00
Total	20.40	28.89	9.58	17.09	18.07	5.98	100.00
(Model)	22.31	31.19	9.55	15.26	15.55	6.14	100.00
	Obese Individuals: $t-1$ in Rows, t in Columns						
	No Work	Prof/Mgr	Sales/Admin	Craftsmen	Ops/Labor	Service	Total
No Work	67.76	11.70	3.57	5.99	6.99	3.99	100.00
(Model)	49.64	10.22	6.34	12.25	14.62	6.94	100.00
Prof/Mgr	3.84	86.84	3.50	3.61	1.41	0.79	100.00
(Model)	1.33	86.56	2.82	3.90	4.16	1.24	100.00
Sales Admin	4.56	11.50	70.99	4.56	6.20	2.19	100.00
(Model)	7.59	11.95	60.63	7.86	9.43	2.54	100.00
Craftsmen	2.28	5.59	1.97	80.24	8.35	1.57	100.00
(Model)	5.25	6.06	3.29	73.59	7.89	3.92	100.00
Ops/Labor	4.44	3.06	3.45	10.26	75.64	3.16	100.00
(Model)	6.73	4.81	5.50	9.96	67.05	5.96	100.00
Service	5.75	4.20	3.10	1.77	5.97	79.20	100.00
(Model)	14.30	9.75	4.98	7.41	9.91	53.65	100.00
Total	11.61	31.34	9.56	21.92	17.49	8.06	100.00
(Model)	9.73	33.53	9.59	21.14	18.86	7.15	100.00

Source: NLSY '79.

into professional occupations from labor and service occupations and underpredicts persistence in the craftsmen, laborer, and service occupations. When individuals are obese, the model underpredicts persistence in not working.

7. SIMULATIONS

Using the estimated parameters from the model, I conduct four counterfactual simulations. I first construct a simulated sample of 100,000 individuals that reflects the distribution of unobserved heterogeneity and initial conditions for years of schooling and body mass. I then simulate wage offers, employment decisions, and weight gain from age 17 onward to establish a baseline. As this is a partial equilibrium model, all of these effects should be interpreted in the context of the individual worker instead of the population.

The first simulation supposes that workers with high body weight became a protected class of worker under equal opportunity employment laws. Under such a policy, "discrimination" on the basis of body weight would be illegal. Would specifying obese workers as a protected class affect wages and occupational choice frequencies? Because the partial equilibrium nature of the model implicitly assumes that employers will not implement any compensating behavior, the results of this simulation should be viewed as the largest possible effect of such a policy.

The model includes job requirements and various costs of employment, acknowledging that body weight affects both worker productivity and the utility from occupational alternatives. However, I posit that two aspects of the individual's employment decision are most likely to be affected by antidiscrimination policies: body-weight-specific occupation switching costs, and the effect of BMI alone on wages.[57] This counterfactual imposes that workers of all BMI will incur no direct wage penalties for their body weight (but can still be paid lower wages for factors that may reflect productivity: job requirements or returns to experience) and will face the same switching costs as healthy weight workers.[58]

The results, as shown in Figure 6, indicate that policies protecting obese workers will substantially, if not entirely, reduce differences in occupational choice frequencies between obese and nonobese workers. As the bottom panel indicates, treating obese workers as a protected class will likely do very little to reduce wage disparities between obese and nonobese workers. Most of the observed growth in wage disparities between obese and nonobese workers stems from job requirements and returns to experience.

We can also use the model to simulate the expected workplace costs of adolescent obesity over the life cycle. I decrease (increase) the individual's body mass at age 17 by 20% (approximately 5 BMI points, or one weight class) in one simulation. Figure 7 contains the results. Individuals with reduced body weight were 10% more likely to gain employment in professional occupations before age 30, relative to the baseline. Simulating the model with a 20% increase in initial body mass, an individual is still 15% less likely to be employed in professional occupations by age 35 and 5% more likely to select either blue-collar occupation (craftsmen or laborer).[59] The final panel in Figure 7 shows that overall, a 20% increase/decrease in initial BMI leads to a 5% decrease/10% increase in real wages over the life course. These results indicate that changes in initial BMI have compounding effects on wages over the life cycle.

The results of this simulation have two important policy implications, both of which provide additional motivation for preventing or reducing adolescent obesity. First, under the neoclassical perspective that wages are determined by productivity, this simulation shows that rising adolescent obesity rates are likely to adversely affect the average productivity of labor in the United States. Second, these results point to adolescent obesity as a likely future cause of income inequality. Structural change in the U.S. economy has not been favorable to blue-collar occupations. The sample period for this article begins around 1980, when the distribution of wages was less skewed and more favorable to blue-collar workers. Therefore, these results may understate the current expected labor market consequences of obesity among adolescents.[60]

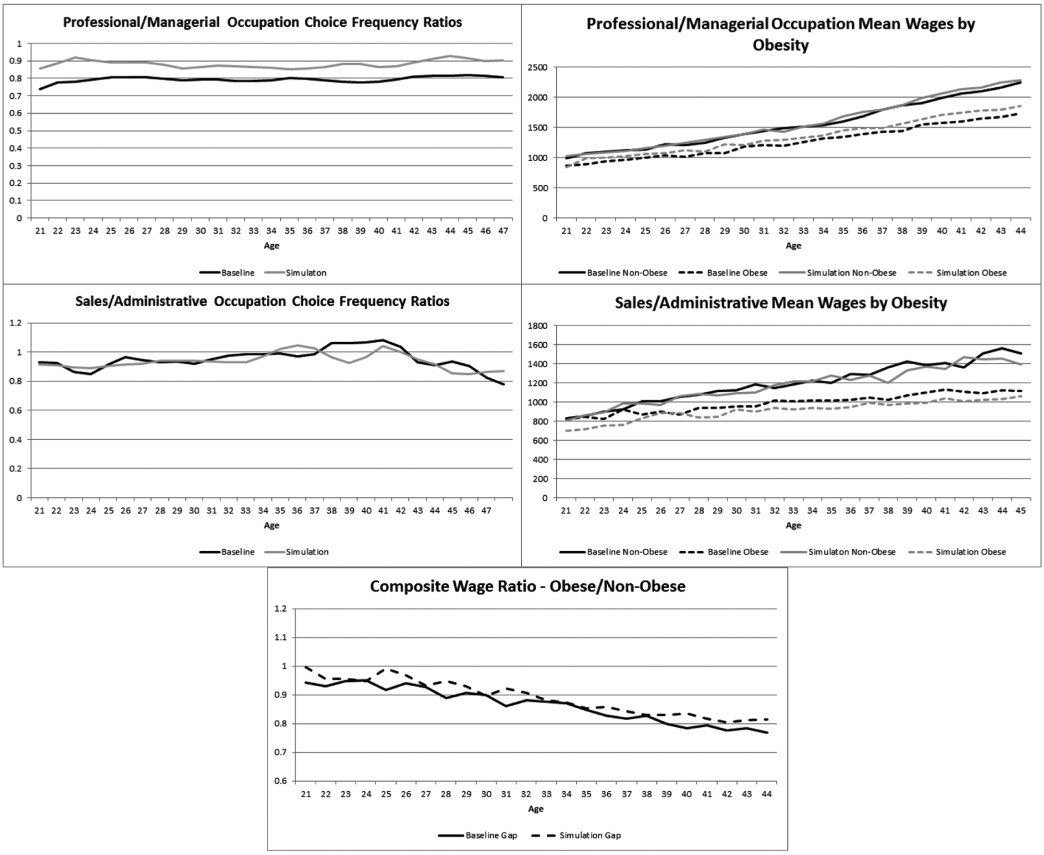
The third simulation examines the effect of changes in the built environment and relative food prices on wages. By simulating a counterfactual condition where the food prices and the retail food environment are held fixed over the sample period at initial values, we can evaluate how changes in the food environment have affected body weight and subsequently wages over

[57] Controlling for the effects of job requirements, returns to education, and returns to experience on body weight-based wage differentials, the parameters characterizing the effect of BMI alone capture the "unexplained" wage penalty for body weight. Similarly, for the nonmonetary costs of employment, controlling for the effects of requirements, education, occupation of origin, and age—the body-weight-specific switching costs are attributed to additional labor demand frictions faced by heavier workers. To conduct this counterfactual, I simulate the model with the parameters of BMI alone in the wage expression and the parameters for switching costs specific to BMI all set to zero. I then compare the means of this simulation to the baseline.

[58] The near certainty that firm compliance would be imperfect underscores the claim that these results should be considered an "upper bound" estimate of the effects of such a policy.

[59] The effects on occupational attainment for SCA jobs were not as pronounced.

[60] Changing norms about body weight may also affect the external validity of this simulation. For example, Pinkston (2015) finds that a history of severe obesity, but not ordinary obesity, predicts lower wages in the NLSY '97 cohort. Therefore, although high body weight among adolescents is a concern, the threshold at which body weight becomes an impediment to labor market success may be increasing with population obesity rates.



NOTES: "Occupaton Choice Frequency Ratio" is the ratio of the emperical frequency with which obese workers select into that occupation to the empirical frequency with which nonobese workers select into that occupation. More formally, Occupation Choice Frequency Ratio can be expressed as $\frac{\sum_h p(d_t^{hj}=1|Obese=1)}{\sum_h p(d_t^{hj}=1|Obese=0)}$.

FIGURE 6

COUNTERFACTUAL RESULTS—DISCRIMINATION POLICY

the sample period.[61] Again, under the neoclassical perspective that wages are determined by productivity, results from this simulation yield insight on how changes in the food environment have affected average productivity of labor.[62]

The results from this simulation are available in Figure 8. Each figure plots ratios of mean wages in each occupation (with the aggregate in the bottom right) by age of the individuals in the simulation. For professional/managerial occupations, shown in the top left panel, the reported wage ratios centered around 1.02 indicate that wages in that occupational category would have been 2% higher had the food environment remained unchanged over the sample period. The largest increases in wages are observed in the sales/administrative and service occupations.

[61] The weight transition results in Table 9 indicate that changes in relative food prices, fast food restaurants, and grocery stores per capita are linked to changes in body weight. Evidence from prior work on the effects of food prices and the food environment is mixed. Courtemanche et al. (2016), Courtemanche and Carden (2009), Salois (2012), and Currie et al. (2010) find that relative food prices, but particularly the built environment, affect BMI and obesity rates. Other studies, including Dunn et al. (2012), Anderson and Matsa (2011), and Dunn (2010), do not find effects of the food environment and relative prices on body weight. Further, the results in Table 9 indicate that the effect of environmental factors on BMI varies strongly over the support of the distribution of BMI. These heterogeneous effects may help explain some of the mixed findings in prior literature.

[62] As the evidence from this and other studies indicates the direct wage penalties for body weight for men are minimal, changes in wages resulting from changes in body weight likely do reflect differences in productivity.

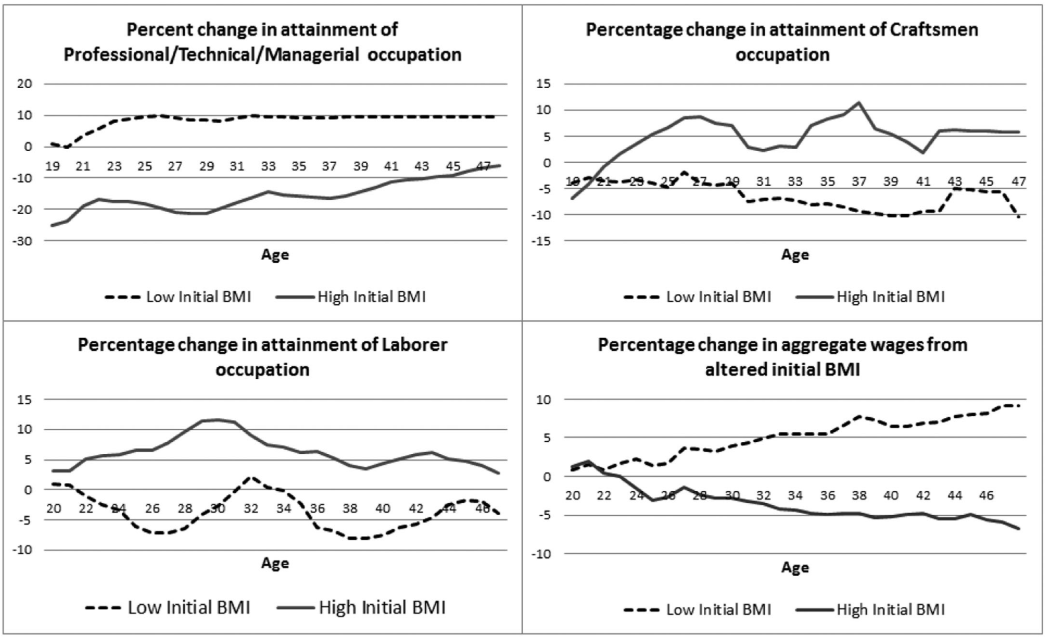


FIGURE 7

COUNTERFACTUAL—EXOGENOUS 20% DECREASE/INCREASE IN INITIAL BMI

Overall, the simulation predicts that changes in the food environment over the sample period may have led to as much as a 3% decrease in wages by age 45.

Finally, to demonstrate the importance of the dynamics in the individual's decision-making process, I simulate the effects of an exogenous one-time shock (a loss of 5 BMI points) to an individual's body weight at age 35.[63] Results are shown in Figure 9. Prior work has found small direct wage penalties' for body weight among men, if any at all. The initial simulated effect of this weight loss wages ($\approx$ 4.5%) is likely overstated due to a feature of the model, as individuals after weight loss will realize immediate higher returns to all prior experience. The main result from this simulation is that the effect of this change in weight is not static and grows over time. By age 45, an individual who lost 5 BMI points at age 35 is expected to earn 10% higher wages than if he had not lost the weight. This increase is driven by both increased occupational mobility into white-collar occupations after the weight loss and increases in expected wages in those occupations. The model predicts that such an exogenous shock would increase wages by approximately \$2.56 in professional occupations and \$2.40 in sales and administrative occupations. The individual is 10% more likely to attain work in a professional or managerial occupation.

8. DISCUSSION

This study formulates and estimates a dynamic stochastic model of employment decisions and wages to determine the full effect of body weight on labor market outcomes. When previous work has focused on attributing weight-based differentials to discrimination, productivity, or other motivations, this article focuses on how monetary and nonmonetary costs of body weight 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

[63] For a 5-foot 8-inch male, this is the equivalent of losing 25 pounds. For a 6-foot-tall male, this equates to losing 29 pounds.

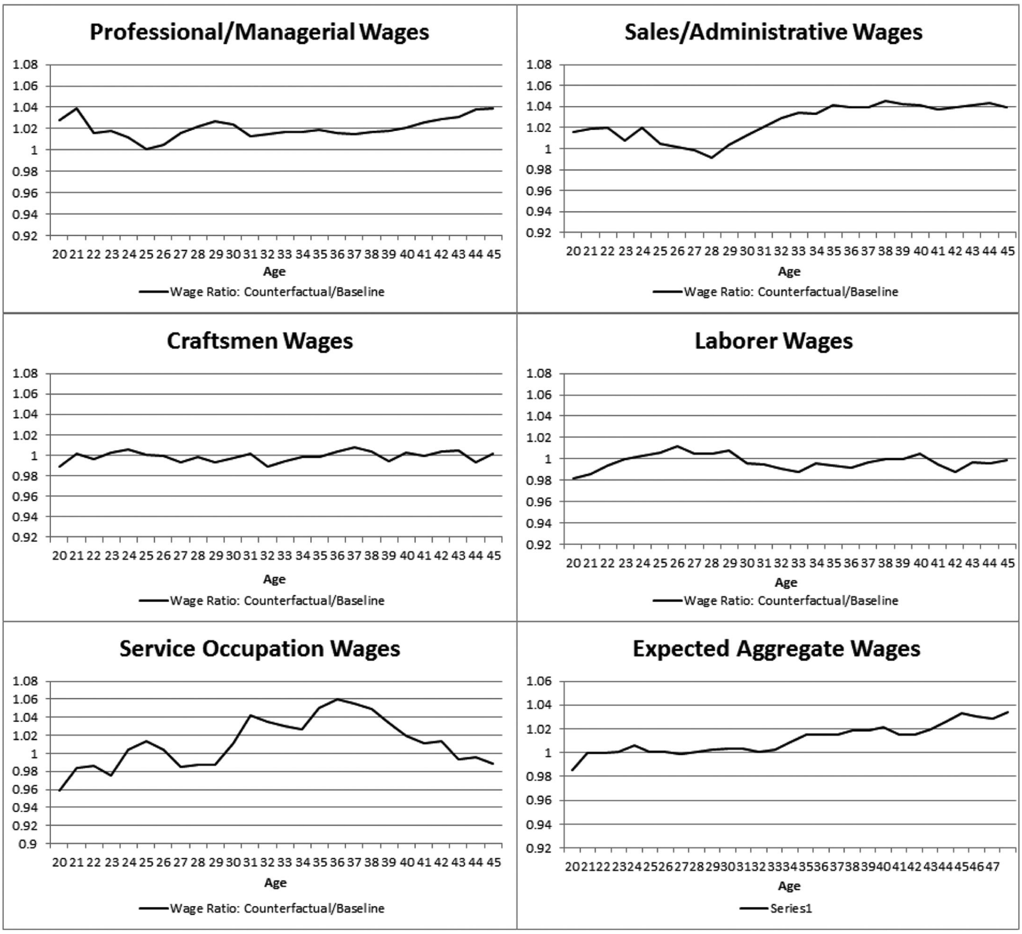


FIGURE 8

COUNTERFACTUAL RESULTS—EFFECTS OF FOOD ENVIRONMENT ON PRODUCTIVITY

white-collar occupations. Body weight leads to lower wages and higher nonmonetary costs in jobs with greater social requirements, but the opposite is true in jobs with intense physical requirements.

The main finding from this article is that static analyses of the effects of body weight on wages, no matter how carefully done, can understate the effects of body weight over the life cycle. Previous work in the literature (e.g., Averett and Korenman, 1996; Cawley, 2004; Han et al., 2009) has found that contemporaneous wage penalties for obesity are small in white males. Although 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. Although 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.

This article also contributes to recent literature on the long-term effects of adolescent obesity on labor market outcomes. Although Han et al. (2011) find that adolescent obesity leads to a 3.5% decrease in mid-career wages (through age 30), Lundborg et al. (2014) decompose an estimated 18% gap in adult wages (aged at least 40) into family characteristics (using

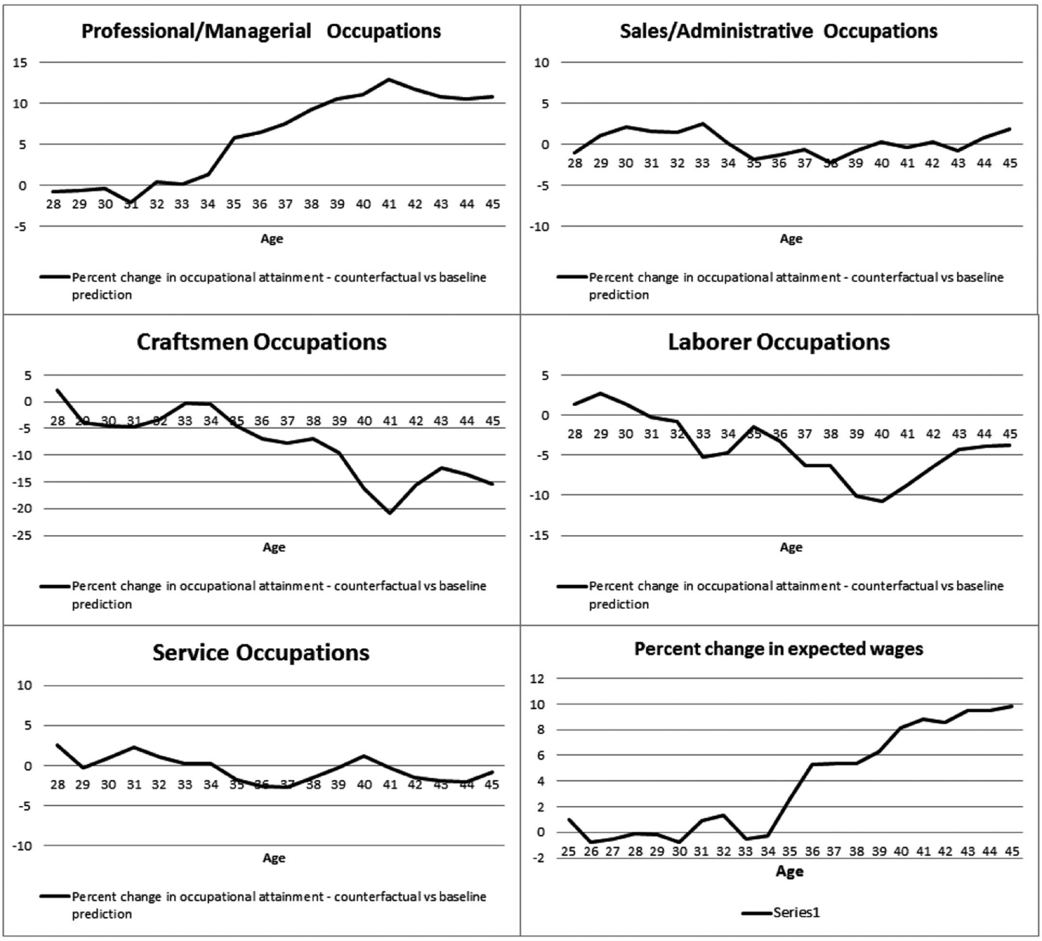


FIGURE 9

COUNTERFACTUAL RESULTS—EXOGENOUS 5-POINT LOSS OF BODY MASS AT AGE 35

sibling differences), occupation controls, and cognitive and noncognitive skills. Although both papers allude to correlations between body weight and employment decisions, neither estimate represents a true counterfactual, because neither paper models the effects of body weight on the individual's occupational choice or the effects of that choice on subsequent wages and alternative-specific values. Simulation results in Section 7 indicate that a 5-BMI-point increase at age 17 leads to 5% lower wages by age 30 (roughly consistent with Han et al., 2011) and 10% by age 45.

Recent work by Lindeboom et al. (2010) and Caliendo and Lee (2013) and experimental work by Reichert (2015) has found that weight or weight loss among men does not affect the probability of gaining employment. Our results are consistent with this overall conclusion, but yield the additional insight that body weight does affect the particular kind of work an individual is likely to attain conditional on wage offers.

Results from this article also offer insights on why contemporaneous wage penalties for obesity are typically found for women, but not men. The common interpretation of this finding is that women suffer "discrimination" when overweight or obese, but men do not. In Table 11, we observe the following occupational choice frequencies for women and men in their early thirties.[64] Note that 59% of men are found in blue-collar or service occupations, in which body

[64] Most early work on this question, consistent with Cawley (2004), only analyzed data up to approximately age 30.

TABLE 11
OCCUPATIONAL CHOICE FREQUENCIES, AGE 30–35 NLSY '79

Occupation	Men	Women
Professional/Managerial	26%	35%
Sales/Administrative	15%	32%
Service	11%	19%
Blue	48%	14%

NOTES: Reproduced from Han et al. (2011).

weight does not affect wages or nonmonetary costs. However, 67% of women are found in the white-collar occupations where body weight does matter, even for men. Therefore, the common finding from prior work in the literature that body weight has workplace consequences for women, but not for men, may be driven by occupation-specific costs of body weight and gender differences in occupational choice frequencies. In the absence of a similar model, estimated for women, gender differences in the costs of high body weight are unknowable.

Results also indicate that body weight could become an increasingly important determinant of income inequality in the future. The ongoing transition to a service-based economy is not good news for heavier people. Given that the generation entering the workforce in the United States is the heaviest yet, these results have negative implications for future average productivity of labor. Further, the share of blue-collar jobs, which favor heavier workers, is shrinking. Results imply that income inequality on the basis of body weight will likely continue to worsen. The findings of this article indicate that prevention and remediation of adolescent obesity has importance beyond curtailing expected future health care costs and that such interventions will likely yield positive externalities for workplace productivity.

SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Table 12: Estimates for State Transitions - Marriage and No. of Children
Table 13: Estimates of Wage Density Parameters
Table 14: Estimates of Wage Density Parameters- BMI Interacted with Experience & Education
Table 15: Parameter Estimates for Body Mass Density
Table 16: DOT Requirement Values and Definitions
Table 17: Occupation categories assumed fixed
Table 18: Regression Results - DOT ratings on O*NET Ratings
Table 19: Summary Statistics - Ratio of Food Prices from ACCRA
Table 20: Simulation - Physical Job Requirements Do Not Affect BMI

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