THREE ESSAYS ON THE DETERMINATION OF LABOR MARKET OUTCOMES IN THE UNITED STATES

by

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THIS DISSERTATION IS HEARTILY DEDICATED

TO MY GRACIOUS, KINDHEARTED, SELFLESS PARENTS,

MR. WAZIULLAH MAJUMDER AND MRS. KARIMUNNESA BEGUM,

WHO BUILT THE STAIR THAT I CLIMBED UP TO REACH THIS STAGE;

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ABSTRACT

In the face of increasing labor market difficulties in the United States (US), it is important to study the determination of labor market outcomes in this country. This dissertation is an effort extended toward that direction. It consists of three chapters covering the effects of various factors on labor market outcomes in the US.

In the first chapter, I draw on the US Census 2000 Public Use Microdata Sample (PUMS) 5% File to examine the effects of homeownership on employment and wages. Empirical strategies used include logit, ordinary least squares (OLS), and the maximum simulated likelihood (MSL) approach. Two instrumental variables are used to strengthen the robustness of estimations. Findings of this chapter suggest that, relative to renters, outright owners are more likely to be employed, and earn higher wages. Mortgagers have higher employment probability compared to renters. However, they are found to be no different than renters in terms of wages.

In the second chapter, I examine whether parenting style has any causal impact on children's adult labor market outcomes using the National Longitudinal Survey of Youth 1997 (NLSY97). Results from logit and OLS estimation suggest that parenting style is an important determinant of labor market success. Among four categories of parenting style, authoritative parenting style (AVPS) is found to be the most beneficial. Permissive parenting style (PPS) is seen to be better than uninvolved parenting style (UPS) only in terms of the number of weeks worked. In terms of other labor market outcomes, it is no different than UPS. On the other hand, authoritarian parenting style (ANPS) and UPS are found to be the same across the series of estimations performed.

The final chapter deals with the effects of obesity on wages drawing on the NLSY97. Obesity is represented by a continuous measure of body mass index (BMI) and BMI splines ($\text{BMI} \geq 30$ for obese, $30 > \text{BMI} \geq 25$ for overweight, $25 > \text{BMI} \geq 18.5$ for healthy weight, and $\text{BMI} < 18.5$ for underweight). Using OLS and fixed-effects (FE) methods, I find that white males receive a wage premium for higher BMI. Wages of all other ethno-gender groups seem to remain unaffected by obesity.

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ABBREVIATIONS

2SLS	Two-stage Least Squares
ANP	Authoritarian Parents
ANPS	Authoritarian Parenting Style
AVP	Authoritative Parents
AVPS	Authoritative Parenting Style
ASVAB	Armed Services Vocational Aptitude Battery
BF	Body Fat
BMI	Body Mass Index
BMISQ	Body Mass Index Squared
CEF	Conditional Expected Function
CPS	Current Population Survey
FE	Fixed Effects
FFM	Fat Free Mass
GDP	Gross Domestic Product
IV	Instrumental Variable
MLE	Maximum Likelihood Estimation
MMNL	Mixed Multinomial Logit
MSA	Metropolitan Statistical Area

MSL	Maximum Simulated Likelihood
NCHS	National Center for Health Statistics
NHANES	National Health and Nutrition Examination Survey
NHIS	National Health Interview Service
NLSY	National Longitudinal Survey of Youth
NLSY79	National Longitudinal Survey of Youth 1979
NLSY97	National Longitudinal Survey of Youth 1997
OLS	Ordinary Least Squares
PIAT	Peabody Individual Achievement Test
PP	Permissive Parents
PPS	Permissive Parenting Style
PSID	Panel Survey of Income Dynamics
PUMS	Public Use Microdata Sample
UCPI	Urban Consumer Price Index
UK	United Kingdom
UP	Uninvolved Parents
UPS	Uninvolved Parenting Style
US	United States
WHO	World Health Organization

OVERALL INTRODUCTION

The United States (US) seems to experience growing labor market difficulties. A better understanding of labor market dynamics will help improve this situation. It is therefore important to investigate factors that determine labor market outcomes. This dissertation, comprising of three chapters, is devoted to finding factors that have causal effects on labor market outcomes in the US.

In the first chapter titled "The Effects of Homeownership on Labor Market Outcomes: Evidence from the United States", I use the US Census 2000 Public Use Microdata Sample (PUMS) 5% File to examine the effects of homeownership on two important labor market outcomes: employment and wages. To obtain more precise estimates, I distinguish between mortgagers (homeowners with mortgage liabilities) and outright owners (homeowners with no mortgage liabilities). I use logit and OLS as baseline specifications in the employment model and the wage model, respectively. The maximum simulated likelihood (MSL) approach is applied in both models to address the problem of potential endogeneity. Identification is strengthened by using two instrumental variables. Findings suggest that, relative to renters, outright owners are more likely to be employed, and earn higher wages. Mortgagers have higher employment probability compared to renters. However, they are found to be no different than renters in terms of wages.

The second chapter is entitled "Does Parenting Style Matter for Labor Market Outcomes? Evidence from the United States". In this chapter, I attempt to investigate whether parenting style has any causal impact on children's adult labor market outcomes using the National Longitudinal Survey of Youth 1997 (NLSY97). Four labor market outcomes, namely, wages, number of weeks worked, number of weeks unemployed, and probability of having white collar job, are considered. Logit and OLS are used as empirical strategies. Findings suggest that parenting style is an important determinant of labor market outcomes. Among four categories of parenting style, authoritative parenting style (AVPS) is found to be the most beneficial. Permissive parenting style (PPS) is seen to be better than uninvolved parenting style (UPS) only in terms of weeks worked. In terms of other labor market outcomes, it is no different than UPS. Authoritarian parenting style (ANPS), on the other hand, seems to remain as good as UPS across the series of estimations performed.

The final chapter, "Does Obesity Matter for Wages? Evidence from the United States", is designed to identify the causal link between obesity and wages. Drawing upon the NLSY97, I examine the effects of obesity on wages by gender and ethnicity. First, an OLS model is estimated. Secondly, a fixed-effects (FE) model is used to remove time invariant unobserved heterogeneity. Finally, the FE specification is further estimated after replacing contemporaneous weight variables by one-year lags of weight variables in order to avoid reverse causality. Body mass index (BMI) is used as a continuous measure of weight and BMI splines are used as binary measures of weight. A large number of variables related to human capital, demographics, family background, and personal attitude are controlled. Findings provide evidence that white males receive a wage premium for higher BMI. Wages of all other ethno-gender groups seem to remain unaffected by obesity.

CHAPTER I

The Effects of Homeownership on Labor Market Outcomes: Evidence from the United States

1 Introduction

Although many Americans suffered nightmares from the housing bubble during the last decade, most still dream of owning a home. According to a recent survey conducted by Coldwell Banker Real Estate, 91% of Americans (93% of homeowners and 83% of renters) feel that homeownership is a part of the American Dream.[1] In an effort to make the dream come true, the United States' government has remained actively involved in promoting homeownership through different policies since the 1930s (Carliner, 1998).[2] However, there is a longstanding debate over the acceptability of government's adherence to such policies at the cost of taxpayers' money.

As a justification for government support of homeownership, proponents point to a range of benefits of homeownership including favorable labor market outcomes, such as wage premiums and an increased probability of employment. Presumably, homeownership brings stability in the lives of homeowners and thus creates opportunities

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[1] Source: http://www.coldwellbanker.com/real_estate/learn/survey_finds_psychological_shift_in_viewing_homeownership, Accessed on July 21, 2012

[2] Federal and state incentives for homeownership can be broadly categorized as tax provisions, subsidies, and facilitation of borrowing for home purchases (Poterba, 1994). Policy interventions in the housing sector result in a substantial amount of burden on the public treasury. Carroll et al. (2011) estimate the cost of housing subsidies at around $304 billion (equivalent to 2.1% of nominal GDP) in 2010. According to the Congressional Committee on Taxation, these tax subsidies lead to around $700 billion foregone government revenue over the five-year period through 2014 (see http://www.nytimes.com/2011/08/17/opinion/why-we-should-end-homeownership-subsidies.html).

in the labor market, leading to better labor market outcomes (Coulson and Fisher, 2002). Besides, as Munch et al. (2008) suggest, homeowners are subject to less mobility and hence are likely to stay longer on their jobs. As a result, they are likely to be more productive. On the other hand, opponents often give reference to the so called Oswald hypothesis. According to this hypothesis, homeownership sets impediments to workers' mobility, increasing unemployment duration (in other words, lessening employment probability at a particular point in time) and lowering wages through poor-quality matches (see Oswald, 1996).

It is apparent from the literature that four econometric issues arise in testing the Oswald hypothesis. First, endogeneity may pose threats in the study of homeownership's impact on labor market outcomes from different sources. For example, labor market outcomes may impact homeownership, giving rise to simultaneity-induced endogeneity. In the face of endogeneity, many studies use instruments which do not appear to be appropriate. Second, most studies adopt ordinary least squares (OLS) and traditional two-stage least squares (2SLS) as empirical strategies. For several reasons, these methods are likely to yield inappropriate estimates in this context. Third, homeowners with and without mortgage liabilities are not the same. For example, they are different in tax treatment. Most studies do not distinguish between them, which may lead to inaccurate estimates. Finally, both employment and wages are vital labor market outcomes. But very few studies investigate both the effects on employment and the effects on wages.

I contribute to the literature by proposing solutions to these problems in one framework. Using the state homeownership rate by race and the state property tax rate as instruments, I estimate the effects of homeownership on both employment and wages. In measuring homeownership, I distinguish between mortgagers (homeowners with mortgage liabilities) and outright owners (homeowners with no mortgage liabilities). I use the maximum simulated likelihood (MSL) approach in order to obtain more appropriate estimates.

Findings suggest that mortgagers and outright owners are more likely to be employed than renters by 1.8 and 0.3 percentage points, respectively. In terms of wages, there is no discernible difference between mortgagers and renters. Outright owners, however, earn 11.3% more relative to renters. These findings clearly contrast with the prediction of the Oswald hypothesis and, as a whole, are suggestive of complementary relations between homeownership and labor market outcomes.

The remainder of this paper is organized as follows. Section 2 provides background. Section 3 describes the data and the variables used in this study. Estimation strategies are discussed in Section 4. Findings and their interpretations are presented in Section 5. The final section contains summary and concluding remarks.

2 Background

The empirical investigation of the link between homeownership and labor market outcomes has received a lot of attention since Oswald (1996) propounded the Oswald hypothesis, which suggests a causal positive relationship between regional homeownership rates and regional unemployment rates. In particular, Oswald (1996) finds that a rise of 10 percentage points in the homeownership rate is accompanied by approximately a 2 percentage points rise in the unemployment rate. He uses macroeconomic data on a number of developed nations including the United States (US), the United Kingdom (UK), Italy, France, and Sweden. In response, researchers began to test the hypothesis at the micro-level. The literature covers a range of labor market outcomes such as labor supply, unemployment duration, job transitions, and wages.

Among early studies, Coulson and Fisher (2002) attempt to measure the effects of homeownership on the probability of being unemployed and wages as well as on the duration of unemployment. Using two US datasets, namely, the Current Population Survey (CPS) and the Panel Survey of Income Dynamics (PSID), they find that homeowners have lower unemployment probabilities, shorter spells of unemployment, and higher wages than renters. Their estimates are potentially inconsistent because they use simple probit and ordinary least squares (OLS), leaving potential endogeneity unaddressed.

Coulson and Fisher (2009), however, end up with a conclusion that is partly contradictory to the findings of their previous study. These authors adopt an instrumental variable (IV) strategy and use data from the US census. The instruments they use are the percentage of households in the metropolitan statistical area (MSA) living in multifamily housing, the state marginal tax rate, and a dummy variable for whether the first two children of a household are of the same sex. They find, in part, support of the Oswald hypothesis: though homeowners are less likely to be unemployed, they earn lower wages.

Using Australian data, Flatau et al. (2003) carry out a variety of estimations and find negative association between homeownership and unemployment in most of the cases. In order to account for endogeneity, they use age dummies and education dummies as instruments. Based on Danish micro data, Munch et al. (2008) examine the impact of homeownership on individual job mobility and wages. Their findings suggest that homeowners enjoy a wage premium of around 5.37% compared to renters. To address possible endogeneity of homeownership, they simultaneously estimate a system of three equations: one for the probability of being a homeowner, one for the transition rates out of job spells, and the other for wages. They use three instruments: the regional homeownership rate, the homeownership status of the parents, and the regional homeownership rate in the region of birth- in the homeownership equation.

Similar to Munch et al. (2008), Morescalchi (2011) jointly estimates treatment choice (homeownership status) equations and the outcome equation to measure the effects of homeownership on the probability of being unemployed and the hazard rate into unemployment. He uses the number of family units within the household, a dummy for whether the first two children are of the same sex, and a regional house price index as instruments. His findings suggest that homeowners with mortgage liability are less likely to be unemployed compared to renters, but there is no discernible difference in unemployment probability between outright owners and renters.

As evident, findings vary in the literature. One reason, presumably, for the varying results is the choice of instruments. In the context of this study, a good instrument requires that it be correlated with homeownership status but uncorrelated with labor market outcome. As Angrist and Krueger (2001) argue, the bias resulting from the use of inappropriate instruments is much greater than the bias in OLS estimates. It seems that the instruments used in the literature are not good enough. For example, Flatau et al.

(2003) use age dummies and education dummies as instruments to account for endogeneity, but empirical evidence suggests that age and education cannot be excluded from an employment equation or a wage equation (see Card, 1999; Dostie, 2011). Coulson and Fisher (2009) propose an instrument of state marginal tax. This instrument is most likely to be correlated with labor market outcomes through channels other than homeownership status. High state marginal tax rates encourage homeownership on the one hand and discourage firms' demand for labor on the other hand.

Secondly, the literature tends to adopt OLS and 2SLS approaches (see Brunet and Lesueur, 2003; Coulson and Fisher, 2002; Coulson and Fisher, 2009). OLS is clearly inappropriate where endogeneity is present. Moreover, the problem with using the traditional 2SLS approach in a model in which the endogenous regressor is discrete is that the resulting estimates are not guaranteed to be efficient. For the estimates to be efficient in such case, the nonlinear specification used in the first stage must be the same as the conditional expected function (CEF) associated with this stage, which can occur only by chance (see Angrist and Pischke, 2009, pp. 190-191).

A third reason for the varying results is that homeownership is measured in a variety of ways. Ignoring the distinction between homeowners with and without mortgage liabilities is an important shortcoming of the current literature. For example, in locations with limited bank competition, all else equal, homeowners may face higher interest rates and may be less likely to have paid off the full balance of the loan. Additionally, labor demand may be affected by higher interest rates. In this case, the distinction between full and partial ownership needs to be accounted for as errors in measurement may cause estimation biases. Besides, the homeowners who have mortgage liabilities may be significantly different from the homeowners who do not have any mortgage liabilities in unobserved ways. Putting all homeowners into one category could cause many important intergroup variations to be lost, giving rise to misleading estimates.

Another shortcoming of the current literature is that the studies outlined above rarely estimate the effects of home ownership on both employment and wages. To be specific, only Coulson and Fisher (2002, 2009) look at the effects on both outcomes. Estimation of the effects of home ownership on both labor market outcomes is important, because it allows a more complete picture of the consequences of homeownership and the tradeoffs between wages and unemployment. For example, Flatau et al. (2003) and Morescalchi (2011) find homeownership causes unemployment to fall. This may not be a favorable labor market outcome, however, if it is also accompanied by a fall in wages. Likewise, Munch et al. (2008) find homeownership causes an increase in wages, which may not be a good labor market consequence if it is accompanied by a rise in unemployment.

Towards this end, my paper re-examines the Oswald hypothesis using two instruments: the state homeownership rate by race and the state property tax rate, which are correlated with housing tenure status but uncorrelated with error terms of outcome equations. Generally three types of endogeneity need to be addressed in the estimation of homeownership effects on labor market outcomes: simultaneity, omitted variable bias/unobserved heterogeneity, and measurement error. I shed some light on each type in Section 4.

To take into account the distinction between homeowners, I categorize respondents into three groups, namely, outright owners, mortgagers, and renters. Homeowners with no mortgage are classified as outright owners; mortgagers are those who own homes but have positive mortgage liabilities; and those who live in rented homes are categorized as renters. Unlike most studies in the literature, I consider both employment and wages as outcome variables in order to obtain a comprehensive picture of labor market consequences of homeownership.

As suggested by Wooldridge (2002, pp. 477-478), a better method to estimate a model with discrete endogenous treatment is the maximum likelihood estimation (MLE), which jointly estimates the parameters of all equations of a system using all the information available in the model. Therefore, I use the MSL approach, which is a simulation-based MLE. Originally developed by Gourieroux et al. (1984), MSL can work with a simultaneous equation system, where several equations are to be jointly estimated. In my case, I estimate a nonlinear system consisting of two tenure-choice equations for my discrete treatment, which is presumably endogenous, and one outcome equation. Such a system with a nonlinear structure hardly has any closed form solution, thereby warranting a numerical solution (Deb and Seck, 2009). MSL facilitates estimating nonlinear models numerically by making use of simulation-based integration. Gourieroux et al. (1984) show that maximizing the simulated log-likelihood is asymptotically equivalent to maximizing the log-likelihood. Thus it is possible to obtain unbiased estimates by using MSL if the number of simulation draws is sufficiently large.

3 Data

3.1 The US Census 2000 Public Use Microdata Sample (PUMS) 5% File

I use data from the US Census 2000 Public Use Microdata Sample (PUMS) 5% File. This dataset is produced from a decennial survey on a cross-sectional sample comprising 5% of US housing units and the people living in them. It covers a considerable number of variables pertaining to different socio-economic characteristics as well as many other aspects of human life including education, family background, and wealth status.

3.2 Sample

Because MSL is computationally very intensive and the US Census contains millions of observations, I randomly draw a 10% sample of observations from the dataset to reduce the computational burden. Then I select a sample based on the following considerations. First, I focus only on those respondents who are household heads. Morscalchi (2011) argues that for modeling homeownership choices, the sample should be comprised of respondents who are responsible for choice decision. Obviously, it is household heads who are to choose among the types of homeownership. Second, as Averett and Korenman (1996) point out, presumably the wages of young workers are highly variable because of their academic enrollment status. Understandably, employment status is also highly variable for young workers. The younger a person is, the more likely he or she is to be enrolled in school. Considering this and following convention, I exclude those below the age 18. Further, since normal retirement age is 65, those of the age above 65 are dropped. Third, labor market behaviors in military professions and those in civil professions are not comparable. Thus respondents working in military jobs are excluded. Fourth, similar reasoning applies to the workers who are self-employed. The self-employed respondents tend to behave differently than those with employee-type jobs, so they are dropped. Finally, I exclude the observations that have missing values for any variable under consideration. The above exclusion criteria yield two samples of 179,881 and 170,316 observations for the employment model and the wage model, respectively.

3.3 Variables

Following convention, I use the natural logarithm of wages and a dummy variable for employment as dependent variables. The US Census 2000 PUMS 5% File reports yearly total pre-tax wage and salary income of each respondent. It also reports whether a respondent is ‘employed’, ‘unemployed’, or ‘not in labor force’. I consider only those of the first two statuses. My dummy variable for employment is equal to 1 if the status is ‘employed’, and 0 if ‘unemployed’.

My key explanatory variable is homeownership status. Since I consider three types of homeownership (renters, mortgagers, and outright owners), the treatment is represented by two dummy variables: one for mortgagers and the other for outright owners. The category of renters is the control group. The US Census 2000 PUMS 5% File reports whether the home in which a respondent lives is owned or being bought or rented. It also reports whether there is any mortgage an owner owes on home properties. I identify the type of homeownership by combining the information on homeownership and mortgage.

It is understandable that respondents with different types of homeownership are different in many observed and unobserved ways. These differences need to be controlled in order to obtain unbiased estimates. In an effort to control for observed heterogeneity, I use a considerable number of explanatory variables in addition to homeownership. The variables measuring demographic characteristics, human capital, and geographic location are controlled for in both the employment and wage models. Since the variables representing industries are not relevant to the employment model, they are controlled for only in the wage model. The demographic variables include dummies for race, gender, and marital status, age, and age squared. Family background is characterized by family size, the number of own-children in the household, the number of own-children under the age of 5 in the household, the age of youngest own-child in the household, and the number of own siblings in the household. The human capital variables include educational attainment and a dummy for academic enrollment status. Geographic location is accounted for by including state dummies and a dummy for whether respondents live in metropolitan areas. Controlling for geographic location is important because more of the outright owners may live in low cost areas, where both real estate values and wages are low. As a result, ignoring location may give rise to the artifact that outright ownership causes lower wages. Finally, I control for industry characteristics in the wage model using a number of dummies each for a particular sector.

3.4 Summary Statistics

The summary statistics for the employment model and the wage model are presented in Table 1 and Table 2, respectively. The tables contain sample means of the variables (except state dummies) under consideration by type of homeownership. Additionally, they present differences in the sample means between types of homeownership. The sample means of state dummies are not reported for brevity.

The unconditional means of the dependent variables suggest statistically significant differences between renters and homeowners in labor market performances. In particular, mortgagers and outright owners are respectively 4 and 2 percentage points more likely to be employed compared to renters. Moreover, these groups seem to earn respectively around 79% (= exp(0.58)-1) and 23% (= exp(0.21)-1) more than renters. Significant differences in labor market performances between the two homeowner groups are also apparent. Outright owners are 2 percentage points less likely to be employed and receive around 30% (= exp(-0.36)-1) lower wages compared to mortgagers. These differences provide a justification for classifying homeowners into groups based on their mortgage liabilities instead of lumping them together into one category.

The remainder of the summary statistics suggests that homeowners (both mortgagers and outright owners) are statistically significantly different from renters in almost all of the explanatory variables. Most importantly, relative to renters, homeowners are older, less likely to be enrolled in school, more likely to be married, and less likely to live in a metropolitan area. Moreover, they have larger families compared to renters. Another important pattern is that, relative to renters, mortgagers have more education, while outright owners have less. Males and whites are in greater proportion among homeowners than among renters. The reverse is true for blacks and Hispanics. Further, sample means of industry dummies, which are present only in the wage model, appear to significantly differ between renters and homeowners.

Differences between mortgagers and outright owners in most of the variables are statistically significant. Relative to mortgagers, outright owners are older, less likely to be married, and less likely to live in a metropolitan area. They have less education, larger family size, and fewer own children living in the household than mortgagers. In addition, they are significantly different from mortgagers in terms of all industry dummies except the dummy for transportation and warehousing and the dummy for utilities.

Several patterns are clear from the summary statistics. First, homeowners are statistically significantly different from renters in almost all of the observed ways considered in this study. Second, the two homeowner groups are also significantly different from each other in most of those observed ways. Finally, relative to renters, homeowners seem to have favorable labor market outcomes, with mortgagers having more favorable outcomes than outright owners. However, this does not necessarily mean that the favorable outcomes are the causal effects of homeownership. To identify the causality, I investigate empirically.

4 Empirical Strategies

4.1 Logit and OLS

I attempt to estimate the causal effects of homeownership on employment and wages. Each outcome is modeled as a function of homeownership and other covariates. I use a dummy for mortgagers and a dummy for outright owners in my models. The dummy for mortgagers assumes a value of 1 if the respondent is a mortgager and 0 otherwise. Similarly, the dummy for outright owners equals 1 if the respondent is an outright owner and 0 otherwise. Renters are the reference group. Accordingly, for an observation of the *i*th respondent, the employment model and the wage model can be represented by

$$y_i = \gamma_1^E h_{1i} + \gamma_2^E h_{2i} + \boldsymbol{\beta^E x_i^E} + \varepsilon_i^E \text{ and} \tag{1}$$

$$\ln w_i = \gamma_1^W h_{1i} + \gamma_2^W h_{2i} + \boldsymbol{\beta^W x_i^W} + \varepsilon_i^W \text{ ,} \tag{2}$$

respectively, where superscripts *E* and *W* stand for the employment model and the wage model, respectively; y_i is a dummy for being employed and $\ln w_i$ is the natural logarithm of wages; h_{1i} and h_{2i} are dummies for mortgagers and outright owners, respectively; $\boldsymbol{x_i}$s are vectors of other covariates; ε_is are the error terms; and γ_1s, γ_2s and $\boldsymbol{\beta}$s are the parameters to be estimated. I am particularly interested in γ_1s and γ_2s because they measure the effects of homeownership.

As a first attempt, I assume Equation (1) to have a logit specification and Equation (2) to have an OLS specification. In the logit specification, y_i takes a value of 1 if the respondent is employed and 0 if unemployed. On the other hand, in the OLS specification, $\ln w_i$ is a continuous variable.

4.2 MSL

The differences among the three groups of respondents (renters, mortgagers, and outright owners) in observable characteristics discussed in Section 3 provide preliminary support to the presumption that those groups are also different in the characteristics that are not observed to researchers. To the extent that these unobserved characteristics affect both labor market outcomes and homeownership status, the estimates will be biased. Moreover, the presence of simultaneity is possible. If a person is employed or earns higher wages, he or she has an incentive to buy a new home or continue ownership of the current home. Further, the presence of classical measurement error cannot be ruled out. Both interviewees and interviewers can make random mistakes in reporting and documenting homeownership status. Simple logit or OLS may not produce unbiased results in the presence of such endogeneity. Thus switching to an appropriate strategy is needed to isolate the true causal effects of homeownership. Given this context, I choose to use the MSL approach because of the reasons spelt out in Section 2.

Following Deb and Trivedi (2006a, 2006b), the indirect utility that the *i*th respondent derives from choosing the *j*th treatment can be expressed as

$$U_{ji}^{*} = \boldsymbol{\alpha_j z_i} + v_{ji}, \quad j = 0,1,2 \tag{3}$$

where $\boldsymbol{z_i}$ is a vector of observed covariates and v_{ji} is the error term. For the sake of simplicity, I assign a zero value for the indirect utility associated with the control group ($j = 0$), i.e. $U_{0i}^{*} = 0$. I assume that the error term v_{ji} contains a latent component, which affects indirect utility as well as outcomes under consideration. Thus Equation (3) can be re-written as

$$U_{ji}^{*} = \boldsymbol{\alpha_j z_i} + \delta_j l_{ji} + \eta_{ji}, \quad j = 1, 2 \tag{4}$$

where l_{1i} and l_{2i} are latent factors associated with the treatment choice equations for mortgagers and outright owners, respectively; δ_1, δ_2 are factor loadings; and η_{ji} are iid error terms. Now, the *i*th respondent chooses the *j*th treatment (being a mortgager or an outright owner) if $U_{ji}^{*} = \boldsymbol{\alpha_j z_i} + \delta_j l_{ji} + \eta_{ji} > 0$. That means the probability of choosing the *j*th choice can be expressed as

$$\Pr\left(h_{ji} = 1 \middle| \boldsymbol{z_i}, l_{ji}\right) = \Pr\left(\boldsymbol{\alpha_j z_i} + \delta_j l_{ji} + \eta_{ji} > 0\right) = \Pr\left(\boldsymbol{\alpha_j z_i} + \delta_j l_{ji} > -\eta_{ji}\right) = \boldsymbol{g}(\boldsymbol{\alpha_j z_i} + \delta_j l_{ji}), \quad (5)$$

where $\boldsymbol{g}(.)$ is a cumulative probability function. Keeping consistency with Equations (1) and (2) and taking latent factors into account, my outcome-generation processes for the employment model and the wage model can be formulated as

$$\mathrm{E}\left(y_i \middle| \boldsymbol{x_i^E}, h_{1i}, h_{2i}, l_{1i}, l_{2i}\right) = \boldsymbol{f}(\gamma_1^E h_{1i} + \gamma_2^E h_{2i} + \boldsymbol{\beta^E x_i^E} + \lambda_1^E l_{1i} + \lambda_2^E l_{2i}) \text{ and} \quad (6)$$

$$\mathrm{E}\left(\ln w_i \middle| \boldsymbol{x_i^W}, h_{1i}, h_{2i}, l_{1i}, l_{2i}\right) = \boldsymbol{f}(\gamma_1^W h_{1i} + \gamma_2^W h_{2i} + \boldsymbol{\beta^W x_i^W} + \lambda_1^W l_{1i} + \lambda_2^W l_{2i}), \quad (7)$$

respectively, where λ_1s and λ_2s are factor loadings. The meanings of other notations are as described before.

The latent factors l_{1i} and l_{2i}, which are separated from the error terms and merged into the deterministic part of the equations, represent unobserved heterogeneity. To be specific, l_{1i} characterizes the features of a mortgager that distinguish him or her from a renter or an outright owner but at the same time are unobserved by researchers. For example, a mortgager may have higher levels of motivation and enthusiasm, which allow him to be courageous enough to buy a home and bear the burden of mortgage liabilities. Similarly, l_{2i} captures the unobserved features in which an outright owner is different from a mortgager or a renter. An outright owner may be more stable. Typically an outright owner is older and hence is expected to have more acquirable skills.

The latent factors are assumed to drive both treatment choices and the outcome, so once they are separated from the error terms, the remaining errors become independent of each other. Thus, for the employment model and the wage model, the joint distribution of the treatment choices and the outcome variable conditional on the latent factors can be expressed as

$$\Pr\left(y_i, h_{ji} = 1 \middle| \boldsymbol{x_i^E}, \boldsymbol{z_i^E}, l_{ji}\right) = \boldsymbol{f}(\gamma_1^E h_{1i} + \gamma_2^E h_{2i} + \boldsymbol{\beta^E x_i^E} + \lambda_1^E l_{1i} + \lambda_2^E l_{2i}) \times \boldsymbol{g}(\boldsymbol{\alpha_j^E z_i^E} + \delta_j^E l_{ji}) \text{ and} \tag{8}$$

$$\Pr\left(\ln w_i, h_{ji} = 1 \middle| \boldsymbol{x_i^W}, \boldsymbol{z_i^W}, l_{ji}\right) = \boldsymbol{f}(\gamma_1^W h_{1i} + \gamma_2^W h_{2i} + \boldsymbol{\beta^W x_i^W} + \lambda_1^W l_{1i} + \lambda_2^W l_{2i}) \times \boldsymbol{g}(\boldsymbol{\alpha_j^W z_i^W} + \delta_j^W l_{ji}), \tag{9}$$

respectively. The unknown latent factors l_{ji} are assumed to be independently and identically distributed draws from the standard normal distribution, so that their joint distribution $\boldsymbol{k_j}$ can be integrated out of the joint density of y_i and h_{ji} and that of $\ln w_i$ and h_{ji}. That means

$$\Pr\left(y_i, h_{ji} = 1 \middle| \boldsymbol{x_i^E}, \boldsymbol{z_i^E}\right) = \int \left[\boldsymbol{f}(\gamma_1^E h_{1i} + \gamma_2^E h_{2i} + \boldsymbol{\beta^E x_i^E} + \lambda_1^E l_{1i} + \lambda_2^E l_{2i}) \times \boldsymbol{g}(\boldsymbol{\alpha_j^E z_i^E} + \delta_j^E l_{ji})\right] \boldsymbol{k_j}(l_{ji}) d(l_{ji}) \text{ and} \tag{10}$$

$$\Pr\left(\ln w_i, h_{ji} = 1 \middle| \boldsymbol{x_i^W}, \boldsymbol{z_i^W}\right) = \int \left[\boldsymbol{f}(\gamma_1^W h_{1i} + \gamma_2^W h_{2i} + \boldsymbol{\beta^W x_i^W} + \lambda_1^W l_{1i} + \lambda_2^W l_{2i}) \times \boldsymbol{g}(\boldsymbol{\alpha_j^W z_i^W} + \delta_j^W l_{ji})\right] \boldsymbol{k_j}(l_{ji}) d(l_{ji}). \tag{11}$$

As suggested by Gourieroux and Monfort (1996), a simulated estimation of the following types can be used to bypass the computational complication associated with the analytical integration in Equations (10) and (11) (also see Deb and Trivedi, 2006a):

$$\widetilde{\Pr}\left(y_i, h_{ji} = 1 \middle| \boldsymbol{x_i^E}, \boldsymbol{z_i^E}\right) = E\left[\boldsymbol{f}(\gamma_1^E h_{1i} + \gamma_2^E h_{2i} + \boldsymbol{\beta^E x_i^E} + \lambda_1^E l_{1i} + \lambda_2^E l_{2i}) \times \boldsymbol{g}(\boldsymbol{\alpha_j^E z_i^E} + \delta_j^E l_{ji})\right] \approx \frac{1}{S}\sum_{s=1}^{S}\left[\boldsymbol{f}(\gamma_1^E h_{1i} + \gamma_2^E h_{2i} + \boldsymbol{\beta^E x_i^E} + \lambda_1^E \tilde{l}_{1is} + \lambda_2^E \tilde{l}_{2is}) \times \boldsymbol{g}(\boldsymbol{\alpha_j^E z_i^E} + \delta_j^E \tilde{l}_{jis})\right] \text{ and} \tag{12}$$

$$\widetilde{\Pr}\left(\ln w_i, h_{ji} = 1 \middle| \boldsymbol{x_i^W}, \boldsymbol{z_i^W}\right) = E\left[\boldsymbol{f}(\gamma_1^W h_{1i} + \gamma_2^W h_{2i} + \boldsymbol{\beta^W x_i^W} + \lambda_1^W l_{1i} + \lambda_2^W l_{2i}) \times \boldsymbol{g}(\boldsymbol{\alpha_j^W z_i^W} + \delta_j^W l_{ji})\right] \approx \frac{1}{S}\sum_{s=1}^{S}\left[\boldsymbol{f}(\gamma_1^W h_{1i} + \gamma_2^W h_{2i} + \boldsymbol{\beta^W x_i^W} + \lambda_1^W \tilde{l}_{1is} + \lambda_2^W \tilde{l}_{2is}) \times \boldsymbol{g}(\boldsymbol{\alpha_j^W z_i^W} + \delta_j^W \tilde{l}_{jis})\right], \tag{13}$$

where S is the number of simulation draws, $\tilde{l}_{jis}$ is the sth draw of pseudo-random numbers from the density $\boldsymbol{k_j}$, and $\widetilde{\Pr}$ is the simulated probability. The simulated log-likelihood functions for the data can be expressed as

$$\ln l\left(y_i, h_{ji} = 1 \middle| \boldsymbol{x_i^E}, \boldsymbol{z_i^E}\right) \approx \sum_{i=1}^{N} \ln\left[\frac{1}{S}\sum_{s=1}^{S}\left[\boldsymbol{f}(\gamma_1^E h_{1i} + \gamma_2^E h_{2i} + \boldsymbol{\beta^E x_i^E} + \lambda_1^E \tilde{l}_{1is} + \lambda_2^E \tilde{l}_{2is}) \times \boldsymbol{g}(\boldsymbol{\alpha_j^E z_i^E} + \delta_j^E \tilde{l}_{jis})\right]\right] \text{ and} \tag{14}$$

$$\ln l\left(\ln w_i, h_{ji} = 1 \middle| \boldsymbol{x_i^W}, \boldsymbol{z_i^W}\right) \approx \sum_{i=1}^{N} \ln\left[\frac{1}{S}\sum_{s=1}^{S}\left[\boldsymbol{f}(\gamma_1^W h_{1i} + \gamma_2^W h_{2i} + \boldsymbol{\beta^W x_i^W} + \lambda_1^W \tilde{l}_{1is} + \lambda_2^W \tilde{l}_{2is}) \times \boldsymbol{g}(\boldsymbol{\alpha_j^W z_i^W} + \delta_j^W \tilde{l}_{jis})\right]\right] \tag{15}$$

for the employment model and the wage model, respectively. Here N is the number of observations. The maximum likelihood estimator solves the following:

$$\arg\max_{\{\Theta^E\}} \sum_{i=1}^{N} \ln\left[\frac{1}{S}\sum_{s=1}^{S}\left[\boldsymbol{f}(\gamma_1^E h_{1i} + \gamma_2^E h_{2i} + \boldsymbol{\beta^E x_i^E} + \lambda_1^E \tilde{l}_{1is} + \lambda_2^E \tilde{l}_{2is}) \times \boldsymbol{g}(\boldsymbol{\alpha_j^E z_i^E} + \delta_j^E \tilde{l}_{jis})\right]\right] \text{ and} \tag{16}$$

$$\arg\max_{\{\Theta^W\}} \sum_{i=1}^{N} \ln\left[\frac{1}{S}\sum_{s=1}^{S}\left[\boldsymbol{f}(\gamma_1^W h_{1i} + \gamma_2^W h_{2i} + \boldsymbol{\beta^W x_i^W} + \lambda_1^W \tilde{l}_{1is} + \lambda_2^W \tilde{l}_{2is}) \times \boldsymbol{g}(\boldsymbol{\alpha_j^W z_i^W} + \delta_j^W \tilde{l}_{jis})\right]\right], \tag{17}$$

where $\Theta^E = \{\gamma_1^E, \gamma_2^E, \boldsymbol{\beta^E}, \lambda_1^E, \lambda_2^E, \boldsymbol{\alpha_0^E}, \boldsymbol{\alpha_1^E}, \boldsymbol{\alpha_2^E}, \delta_0^E, \delta_1^E, \delta_2^E\}$ and

$\Theta^W = \{\gamma_1^W, \gamma_2^W, \boldsymbol{\beta^W}, \lambda_1^W, \lambda_2^W, \boldsymbol{\alpha_0^W}, \boldsymbol{\alpha_1^W}, \boldsymbol{\alpha_2^W}, \delta_0^W, \delta_1^W, \delta_2^W\}$.

To comply with the MSL framework, I assume a mixed multinomial logit (MMNL) specification for treatment choice equations. In particular, Equation (5) is assumed to have the following specific forms

$$\Pr\left(h_{ji} = 1 \middle| \boldsymbol{z_i^E}, l_{ji}\right) = \frac{\exp\left(\boldsymbol{\alpha_j^E} \boldsymbol{z_i^E} + \delta_j^E l_{ji}\right)}{1 + \sum_{m=1}^{2} \exp\left(\boldsymbol{\alpha_m^E} \boldsymbol{z_i^E} + \delta_j^E l_{mi}\right)}, \; j = 1,2 \text{ and} \qquad (18)$$

$$\Pr\left(h_{ji} = 1 \middle| \boldsymbol{z_i^W}, l_{ji}\right) = \frac{\exp\left(\boldsymbol{\alpha_j^W} \boldsymbol{z_i^W} + \delta_j^W l_{ji}\right)}{1 + \sum_{m=1}^{2} \exp\left(\boldsymbol{\alpha_m^W} \boldsymbol{z_i^W} + \delta_j^W l_{mi}\right)}, \; j = 1,2 \qquad (19)$$

for the employment model and the wage model, respectively. Since, for the outcome equation, a logit specification is assumed when outcome is employment and a normal (OLS) specification is assumed when outcome is logarithm of wages, Equations (6) and (7) are assumed to have the specific forms of

$$\Pr\left(y_i = 1 \middle| \boldsymbol{x_i^E}, h_{1i}, h_{2i}, l_{1i}, l_{2i}\right) = \frac{\exp(\gamma_1^E h_{1i} + \gamma_2^E h_{2i} + \boldsymbol{\beta^E} \boldsymbol{x_i^E} + \lambda_1^E l_{1i} + \lambda_2^E l_{2i})}{1 + \exp(\gamma_1^E h_{1i} + \gamma_2^E h_{2i} + \boldsymbol{\beta^E} \boldsymbol{x_i^E} + \lambda_1^E l_{1i} + \lambda_2^E l_{2i})} \text{ and} \qquad (20)$$

$$\mathrm{E}\left(\ln w_i \middle| \boldsymbol{x_i^W}, h_{1i}, h_{2i}, l_{1i}, l_{2i}\right) = \gamma_1^W h_{1i} + \gamma_2^W h_{2i} + \boldsymbol{\beta^W} \boldsymbol{x_i^W} + \lambda_1^W l_{1i} + \lambda_2^W l_{2i}, \qquad (21)$$

respectively.

The parameters under consideration are identified by the nonlinear structure in the treatment choice equations even in the absence of exclusion restrictions (Coulson and Fisher, 2009; Deb and Trivedi, 2006a; Deb and Trivedi, 2006b). In other words, having the same set of variables in the vectors $\boldsymbol{x_i}$ and $\boldsymbol{z_i}$ is not an obstacle to the identification of the parameters. It is, however, recommended to use exclusion restrictions by including instruments in the treatment choice equations for more robust identification (Deb and Trivedi, 2006a; Deb and Trivedi, 2006b).

Based on the above notion, I include two exclusion restrictions when using the MSL approach. The two instruments that I use are the state homeownership rate by race and the state property tax rate. The probability of owning home is supposed to be positively and negatively correlated with the state homeownership rate by race and the state property tax rate, respectively, which is somewhat evident from the data. Shown in Tables 1 and 2, there are statistically significant variations in the sample means of the two instruments between the types of housing tenure. For example, in the sample of the employment model, the differences in mean of state homeownership rate by race between renters and mortgagers, renters and outright owners, and mortgagers and outright owners are 6.63, 7.94 and 1.30, respectively. In the sample of the wage model, the corresponding figures are 6.26, 7.62 and 1.35. Table 3 summarizes the marginal effects of the instruments and their joint significance in the treatment equations. For both models, the state property tax rate is individually insignificant in the equation for mortgagers and significant in the equation for outright owners, but state homeownership rate by race is individually significant in both the equations. Moreover, the chi-square tests suggest that the instruments are jointly significant at the 1 percent level in each of the cases. Thus it is clear that the instruments satisfy the first requirement of good instruments; they substantially explain housing tenure. As far as the second requirement is concerned, there is no reason why the two instruments should affect employment or wages significantly through channels other than housing tenure.

5 Empirical Results

5.1 The Probability of Being Employed

The key results for different specifications of the employment model are presented in Table 4. The marginal effects from a logit regression without any controls are reported in column 1. Being positive and highly significant, these estimates suggest that unconditionally, mortgagers and outright owners are respectively 3.9 and 1 percentage points more likely to be employed than renters. Since homeownership is highly likely to be correlated with other covariates, these estimates might not represent the causal effects. However, they are used as benchmarks in order to see how the estimates change as controls are gradually added.

Columns 2, 3, 4, and 5 show how the marginal effects of homeownership change as demographic, family background, human capital, and geographic controls, respectively, are added as other covariates in the logit regression. After introducing demographic variables, the marginal effects of the dummy for mortgagers and the dummy for outright owners decline to 0.025 and 0.002, respectively. Moreover, the latter loses statistical significance. No changes appear in the marginal effects as family background variables are added in column 3. As human capital variables and geographic variables are added in columns 4 and 5, respectively, the marginal effect of the dummy for mortgagers gradually declines and eventually reaches 0.018. On the other hand, the marginal effect of the dummy for outright owners rises to 0.003 and regains statistical significance with the inclusion of human capital variables. It then remains unchanged after the inclusion of geographic variables in column 5. Thus it turns out that once selection on observables are accounted for, the probabilities of being employed for mortgagers and outright owners are found to be respectively 1.8 and 0.3 percentage points higher than the probability of being employed for renters. However, as argued earlier, these estimates may be biased due to potential endogeneity.

To account for endogeneity, I re-estimate the model using the MSL approach with and without instruments. The marginal effects are displayed in columns 6 and 7 respectively. It appears that the coefficients are the same regardless of whether instruments are included or not. Besides, while both the marginal effects undergo a sizable change in magnitude attributable to the change in model specification (from logit to MSL), the marginal effect of being a mortgager loses statistical significance. To be specific, mortgagers and renters are now not significantly different in terms of employment probability, but outright owners are found to be 1.1 percentage points more likely to be employed relative to renters.

Most importantly, however, although one of the two λ parameters (factor loadings in outcome equation) is individually significant, the log-likelihood ratio suggests that those parameters are not jointly significant. As a result, the null hypothesis of exogeneity cannot be rejected (see Deb and Trivedi, 2006a), which implies that the simple logit specification is good enough to measure the effects of homeownership on the probability of being employed.

Thus I can rely on the results from simple logit specification, which suggest that, relative to renters, both mortgagers and outright owners have a higher probability of being employed. When comparing mortgagers and outright owners, the latter has less likelihood of being employed than the former. These findings are essentially in sharp contrast to the Oswald hypothesis. The interpretation of such findings can go as follows. As already noted, homeownership brings stability in a mortgager's life, which in turn enhances the probability of employment by boosting a person's determination and commitment in the process of job searching. Besides, out of the eagerness not to default on mortgage, a mortgager tends to make every effort to find a job while he or she is unemployed or to remain in the current job while he or she is already employed. This gives rise to a positive impact on the probability of employment. Also, as a homeowner, a mortgager has lower reservation wages for local jobs than a renter (Munch et al. 2006). Lower reservation wages in turn leads to a higher probability of employment. The gross positive impact resulting from stability, eagerness to find a job, and lower reservation wages may well-exceed the negative impact on the employment probability of relative immobility due to higher opportunity cost of moving. In addition, as argued earlier, homeowners are less likely to change jobs and hence they may be potentially more productive, which increases employment probability. As a homeowner, the mortgager benefits from this. As a whole, the net positive effect for a mortgager may be large enough to outweigh the positive effect of the ease of mobility on the employment probability that a renter enjoys.

In the case of an outright owner, there are benefits of stability and a lower job-change probability as opposed to the negative impact of less mobility. But the incentive to put additional effort for a job in order to be able to pay mortgage, that a mortgager has, is absent in the case of an outright owner. In addition, as Flatau et al. (2002) suggest, an outright owner may set higher reservation wages than a renter due to strong housing equity positions, leading to a lower employment probability. Therefore, the net positive effect for an outright owner may only moderately exceed the positive effect accrued to a renter due to higher mobility. Thus it is not surprising that outright ownership generates less additional employment probability compared to ownership with mortgage liabilities.

5.2 Wages

Table 5 presents the key results for the wage model using an estimation approach similar to one used in the employment model. Column 1 contains the results from an OLS regression that uses only the two dummies for homeownership as explanatory variables. These results show that homeownership has statistically significant and large positive effects on wages. Mortgagers and outright owners appear to earn respectively 78.6% and 23.4% more than renters. Since these differences are unconditional, they are likely to be biased.

To explore the robustness of the results, I re-estimate the OLS regression successively including demographic, family background, human capital, industry, and geographic controls. Resulting estimates are presented in columns 2, 3, 4, 5, and 6, respectively. The estimated effects of both being a mortgager and being an outright owner are found to change after adding each group of controls and finally fall to as low as 0.311 and 0.130, respectively, when all of the covariates are included in column 6. However, the statistical significance of both of the estimated effects holds in each regression. The drastic changes in the estimates are suggestive of selection on observables.

The final two columns report the results from my preferred specification, in which I re-estimate the model using the MSL approach with and without instruments. Switching from OLS to MSL causes changes in the magnitudes of the estimates, suggesting the presence of endogeneity bias, but it does not alter the signs. Regardless of whether instruments are included or not, the estimated effect of being a mortgager loses significance, while the other estimate remains significant as in the cases of OLS. Particularly speaking, no discernible differences in wages appear between mortgagers and renters, but outright owners are found to have wages that are higher than renters. They are predicted to earn 13.1% higher in the absence of instruments and 11.7% higher in the presence of instruments. Considering robustness I prefer to accept the results found from MSL with instruments.

In the MSL specification with instruments, the factor loading λ_1 appears to be individually significant, while the factor loading λ_2 is insignificant. However, they are jointly highly significant, which allows to reject the null hypothesis of the treatment variables being exogenous. Thus MSL can be taken as superior to OLS in measuring the effects of homeownership on wages.

The evidence that outright owners receive a wage premium and mortgagers neither receive a wage premium nor suffer a wage penalty may be explained as follows. As pointed out earlier, as a homeowner, a mortgager gains stability and is less likely to change jobs, which presumably tends to increase productivity as well as wages. Further, lower reservation wages as well as a dire need of a job tend to yield lower wages for a mortgager. It is not surprising that these two countervailing effects cancel out each other leaving a mortgager with neither a wage premium nor a wage penalty. Similarly, the fact that outright owners earn more than renters is also not surprising. As mentioned before, an outright owner sets higher reservation wages, which leads to a better job match. Besides, more stability, less likelihood of job-change and more acquirable skills make an outright owner more productive. Therefore, an outright owner is likely to have higher wages as a consequence of better match and higher productivity.

6 Summary and Conclusion

This paper attempts to examine the magnitude and the nature of the causal effects of homeownership on employment and wages to address the ongoing debate among the US policy makers about whether promoting homeownership is justified. Although there is a fairly large body of literature on the effects of homeownership on labor market outcomes, the effects on employment probability and wages remain relatively unexplored. Most importantly, several econometric issues in the previous studies are identified. Many of the instruments used in the literature seem to be questionable. A large portion of the literature uses traditional identification strategies, such as OLS and 2SLS. OLS does not provide unbiased estimates in the presence of endogeneity. 2SLS is also not appropriate for investigating the effects of a discrete and potentially endogenous treatment variable on labor market outcomes. Most studies lump two homeowner groups, mortgagers and outright owners, into one category, thereby leading to less accurate estimates. Moreover, very few studies look at the effects on both employment and wages, whereas both are important labor market outcomes.

In this study, I seek to offer solutions to these problems in one framework. Using the state homeownership rate by race and the state property tax rate as instruments, I estimate the effects of homeownership with and without mortgage liabilities on employment probability and wages. Two specifications are considered for both employment and wage. The baseline specifications for the employment model and the wage model are logit and OLS, respectively. MSL is used as the final specification for both the models. A considerable number of relevant covariates are controlled for in each model.

For the most part, my findings run counter to the Oswald hypothesis. The main prediction of this hypothesis is that homeownership causes unemployment. On the contrary, I find both mortgagers and outright owners have a higher probability of being employed than renters. One implication of Oswald hypothesis is that wages are negatively affected by homeownership, but I find outright owners to earn higher wages than renters. Mortgagers, however, appear neither to receive a wage premium nor to suffer a wage penalty compared to renters.

As a whole, my empirical results imply significant favorable effects of homeownership on labor market outcomes, strengthening the justification for the existing US policies that promote homeownership.

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TABLES

Table 1: Summary statistics: sample for the employment model

Variables	Sample means			Differences in sample means		
	Renters	Mortgagers	Outright owners	Renters vs. mortgagers	Renters vs. outright owners	Mortgagers vs. outright owners
Dependent variable						
Dummy for employment	0.94	0.98	0.95	0.04**	0.02**	-0.02**
Instrumental variable						
State homeownership rate by race	61.85	68.48	69.78	6.63***	7.94***	1.30***
State property tax rate	11.81	11.79	11.65	-0.01	-0.16***	-0.15***
Human capital						
Education	6.94	7.67	6.75	0.73**	-0.19**	-0.92**
Dummy for enrollment	0.10	0.05	0.03	-0.05**	-0.07**	-0.02**
Demographics						
Dummy for male	0.57	0.76	0.72	0.20**	0.15**	-0.04**
Dummy for white	0.66	0.85	0.86	0.19**	0.20**	0.01**
Dummy for black	0.19	0.09	0.08	-0.10**	-0.11**	-0.01*
Dummy for Hispanic	0.15	0.07	0.07	-0.09**	-0.09**	-0.01**
Dummy for married	0.34	0.71	0.61	0.37**	0.27**	-0.10**
Age	36.50	43.24	47.59	6.75**	11.09**	4.35**

Table 1 (Continued)

Variables	Sample means			Differences in sample means		
	Renters	Mortgagers	Outright owners	Renters vs. mortgagers	Renters vs. outright owners	Mortgagers vs. outright owners
Family Background						
Family size	2.31	2.99	2.51	0.68**	0.20**	-0.48**
Number of own children in household	0.85	1.15	0.76	0.31**	-0.08**	-0.39**
Number of own children under age 5 in household	0.23	0.22	0.11	-0.01*	-0.12**	-0.11**
Age of youngest own child in household	58.52	45.24	61.87	-13.28**	3.36**	16.63**
Number of own siblings in household	0.04	0.02	0.02	-0.02**	-0.02**	0.003*
Geographic						
Dummy for metropolitan area	0.74	0.70	0.46	-0.04**	-0.28**	-0.24**
N	60,437	96,642	22,834	-	-	-

* Significant at the 5% level ** Significant at the 1% level

Table 2: Summary statistics: sample for the wage model

Variables	Sample means			Differences in sample means		
	Renters	Mortgagers	Outright owners	Renters vs. mortgagers	Renters vs. outright owners	Mortgagers vs. outright owners
Dependent variable						
Log of wage	10.00	10.58	10.21	0.58**	0.21**	-0.36**
Instrumental variable						
State homeownership rate by race	62.30	68.56	69.92	6.26***	7.62***	1.35***
State property tax rate	11.82	11.79	11.66	-0.03	-0.16***	-0.13***
Human capital						
Education	7.03	7.70	6.80	0.67**	-0.23**	-0.90**
Dummy for enrollment	0.10	0.05	0.03	-0.05**	-0.07**	-0.02**
Demographics						
Dummy for male	0.58	0.77	0.73	0.19**	0.15**	-0.04**
Dummy for white	0.67	0.85	0.86	0.18**	0.19**	0.01**
Dummy for black	0.18	0.09	0.08	-0.09**	-0.10**	-0.01*
Dummy for Hispanic	0.15	0.07	0.06	-0.08**	-0.09**	-0.01**
Dummy for married	0.35	0.72	0.62	0.37**	0.27**	-0.10**
Age	36.57	43.21	47.67	6.64**	11.10**	4.46**
Family Background						
Family size	2.28	2.99	2.51	0.71**	0.22**	-0.48**
Number of own children in household	0.82	1.16	0.76	0.34**	-0.06**	-0.39**
Number of own children under age 5 in household	0.22	0.22	0.11	0.01*	-0.11**	-0.11**
Age of youngest own child in household	59.45	45.12	61.78	-14.32**	2.34**	16.66**
Number of own siblings in household	0.04	0.02	0.02	-0.02**	-0.02**	0.003*

Table 2: (continued)

Variables	Sample means			Differences in sample means		
	Renters	Mortgagers	Outright owners	Renters vs. mortgagers	Renters vs. outright owners	Mortgagers vs. outright owners
Industries						
Dummy for agriculture, forestry, fishing and hunting	0.02	0.01	0.02	-0.01**	0.01**	0.01**
Dummy for mining	0.00	0.01	0.02	0.003**	0.01**	0.01**
Dummy for construction	0.07	0.07	0.09	0.01**	0.02**	0.02**
Dummy for wholesale trade	0.04	0.05	0.04	0.01**	0.005**	-0.01**
Dummy for retail trade	0.11	0.08	0.0.09	-0.02**	-0.01**	0.01**
Dummy for transportation and warehousing	0.05	0.06	0.06	0.01**	0.01**	-0.002
Dummy for utilities	0.01	0.02	0.02	0.01**	0.01**	0.001
Dummy for information and communication	0.04	0.04	0.02	-0.003**	-0.01**	-0.01**
Dummy for finance, insurance, real estate, and rental and leasing	0.07	0.07	0.04	0.00	-0.03**	-0.03**
Dummy for professional, scientific, management, administrative, and waste management service	0.09	0.08	0.05	-0.02**	-0.04**	-0.03**
Dummy for education, health and social services	0.18	0.16	0.17	-0.03**	-0.01**	0.01**
Dummy for arts, entertainment, recreation, accommodations, and food services	0.09	0.03	0.04	-0.06**	-0.05**	-0.01**
Dummy for other services	0.05	0.03	0.04	-0.02**	-0.01**	-0.04**
Dummy for public administration	0.05	0.08	0.0.06	0.03**	0.01**	-0.02**
Geographic						
Dummy for metropolitan area	0.75	0.70	0.46	-0.04**	-0.28**	-0.24**
N	55,291	93,706	21,349	-	-	-

* Significant at the 5% level ** Significant at the 1% level

Table 3: Marginal effects of instruments and their joint significance tests in treatment choice equations

	Employment model		Wage model	
	Equation for mortgagers	Equation for outright owners	Equation for mortgagers	Equation for outright owners
State homeownership rate by race[a]	0.006** (0.000)	0.003** (0.000)	0.006** (0.000)	0.003** (0.000)
State property tax rate[a]	0.001 (0.002)	-0.004** (0.001)	0.002 (0.002)	-0.004** (0.001)
Joint significance test (χ^2)[b]	386.10** (0.000)	325.85** (0.000)	350.11** (0.000)	283.52** (0.000)

[a] Figures in parentheses are robust standard errors .
[b] Figures in parentheses are p-values .
** Significant at the 1% level

Table 4: Results of estimation: the probability of being employed[a]

	Logit					MSL without instruments	MSL with instruments
	1	2	3	4	5	6	7
Mortgagers	0.039** (0.001)	0.025** (0.001)	0.025** (0.001)	0.019** (0.001)	0.018** (0.001)	0.009 (0.005)	0.009 (0.005)
Outright owners	0.010** (0.001)	0.002 (0.001)	0.002 (0.001)	0.003* (0.001)	0.003** (0.001)	0.011** (0.002)	0.011** (0.002)
λ_1	-	-	-	-	-	0.334 (0.207)	0.350 (0.203)
λ_2	-	-	-	-	-	-0.494** (0.146)	-0.454** (0.142)
Log-likelihood ratio	-	-	-	-	-	-1076235 (1.00)	-1076249 (1.00)
Demographic controls?	✗	✓	✓	✓	✓	✓	✓
Family background?	✗	✗	✓	✓	✓	✓	✓
Human capital controls?	✗	✗	✗	✓	✓	✓	✓
Geographic controls?	✗	✗	✗	✗	✓	✓	✓
N	179,881	179,881	179,881	179,881	179,881	179,881	179,881

[a] For 'mortgagers' and 'outright owners', marginal effects are reported. For λs, coefficients are reported. Figures in parentheses in the first four rows are robust standard errors. Figure in parenthesis in the fifth row is p-value.
*Significant at the 5% level ** Significant at the 1% level

Table 5: Results of estimation: wages[a]

	OLS						MSL without instruments	MSL with instruments
	1	2	6	7	5	6	7	8
Mortgagers	0.786** (0.005)	0.408** (0.005)	0.421** (0.005)	0.328** (0.005)	0.292** (0.005)	0.311** (0.005)	0.014 (0.010)	0.019 (0.010)
Outright owners	0.234** (0.008)	0.024** (0.008)	0.033** (0.008)	0.068** (0.007)	0.050** (0.007	0.130** (0.010)	0.131** (0.011)	0.117** (0.013)
λ_1	-		-	-	-	-	0.313** (0.011)	0.302** (0.011)
λ_2	-		-	-	-	-	-0.027* (0.009)	-0.006 (0.012)
Log-likelihood ratio	-		-	-	-	-	4601 (0.000)	4057** (0.000)
Demographic controls?	✗	✓	✓	✓	✓	✓	✓	✓
Family background?	✗	✗	✓	✓	✓	✓	✓	✓
Human capital controls?	✗	✗	✗	✓	✓	✓	✓	✓
Industry dummies?	✗	✗	✗	✗	✓	✓	✓	✓
Geographic controls?	✗	✗	✗	✗	✗	✓	✓	✓
N	170,316	170,316	170,316	170,316	170,316	170,316	170,316	170,316

[a] For ‘mortgagers’ and ‘outright owners’, reported are the percentage changes (when multiplied by 100) in wage due to change in treatment status from renter to other choices. For λs, coefficients are reported. Figures in parentheses in the first four rows are robust standard errors. Figure in parenthesis in the fifth row is p-value.

* Significant at the 5% level ** Significant at the 1% level

CHAPTER II

Does Parenting Style Matter for Labor Market Outcomes? Evidence from the United States

1 Introduction

The impact of family background on children's outcomes appears to have gained increasing attention and interest. One of the most important family background variables is parenting style.[1] A key issue is the extent to which parenting style influences children's labor market outcomes in their adulthood. Most of the parenting style literature overlooks such investigation of the lasting impact of how parents rear their children perhaps due to lack of suitable data that permit linking childhood events to outcomes in adult years.

In this paper, I draw upon the National Longitudinal Survey of Youth 1997 (NLSY97), which contains information about both childhood and adulthood events, to investigate the implications of parenting style for adult labor market outcomes. Particularly, I look at whether parenting style children experience in their childhood has any significant effects on wages, number of weeks worked, number of weeks unemployed, and probability of having white collar job experienced by them in their adulthood. The nature and contents of the data allows me fairly well to identify these effects.

[1] Parenting style is a psychological strategy used by parents in rearing their children. Darling and Steinberg (1993, pp. 448) define parenting style as the emotional climate created by parents within which socialization of children occurs.

Motivation for this study lies in the concern about whether there should be public interventions in the area of child development in terms of promoting parent education and training programs. Justification for funding such programs needs information about associated costs and benefits. This study potentially will be of help in that regard.

The results of this study will have important policy implications. If the relation under investigation is found to be statistically significant, that will mean parenting style has economic consequences in terms of children's adult labor market outcomes. In that case, government should take those consequences, be they costs or benefits, into account while designing policy interventions aimed at shaping parenting style.

The remainder of this paper is laid out as follows. Section 2 outlines a background on the issues under study. Section 3 analyzes the data used in my estimation. Section 4 sheds light on the econometric framework used in the analysis. The empirical results are provided in Section 5. An overall discussion of the findings is presented in Section 6. The final section contains summary and concluding remarks.

2 Background

It is Baumrind (1966) who for the first time proposes three prototypes of parenting styles, namely, authoritative, authoritarian, and permissive. Subsequently, Maccoby and Martin (1983) extend Baumrind's typology to include an additional category- uninvolved. The extended typology is based on two global dimensions of parenting: demandingness and responsiveness. Maccoby and Martin cross these two parenting dimensions to identify four categories of parenting style. A parent is identified as authoritative if he/she is high in both demandingness and responsiveness. An authoritarian parent is one who is high in demandingness but low in responsiveness. If one is low in demandingness and high in responsiveness then he/she is identified as permissive. Finally, one is categorized as uninvolved if he/she is low in both demandingness and responsiveness. Figure 1 summarizes the classification scheme.

Development of the parenting style typology was mainly meant for research on family socialization practices during childhood (Glasgow et al., 1997). This is reflected in the fact that most of the previous research that uses parenting style as a variable belongs to the fields of psychology and family affairs. However, some works can be traced in the areas of adolescent functioning (Glasgow et al., 1997).

Survey of the literature suggests that parenting style affects a wide range of children's outcomes. For example, compared to non-authoritative parenting style, authoritative parenting style foster psychological competence and educational attainment, and reduce internal distress and problem behavior (Baumrind, 1989, 1991; Bornstein and Bornstein, 2007; Dornbusch et al., 1987; Kim and Rohner, 2002; Lamborn et al., 1991; Steinberg et al., 1989; Steinberg et al., 1991; Steinberg et al., 1992; Steinberg et al., 1994). Uninvolved parenting style is found to have the worst impacts in terms of social competence, educational attainment, and psychological adjustment (Baumrind, 1991; Lamborn et al., 1991; Pittman and Chase-Lansdale, 2001; Weiss and Schwarz, 1996). Also, parenting style is found to matter for substance use and health risk behaviors (Jackson et al., 1994; Jackson et al., 1998; Coombs and Landsverk, 1988; Steinberg et al., 1994; Weiss and Schwarz, 1996). Even children's dietary behaviors are documented to be affected by parenting style. For example, Kremers et al. (2003) demonstrate that adolescents raised with an authoritative parenting style have better fruit consumption behavior and fruit-specific cognitions compared to those raised with other parenting styles. They find children of permissive parents to consume more fruits than children of uninvolved and authoritarian parents. Arredondo et al. (2006) shows children's eating behavior and physical activity to be associated with parenting style. The literature also suggests that parenting style is predictive of children's many other aspects such as their strategies for academic achievement (Aunola et al., 2000), psychological disorder and family connectedness (Dwairy et al., 2006), various psychiatric symptoms and personal discomfort of physical status (Xia and Qian, 2001), self-regulation (Grolnick and Ryan, 1989), self-esteem (Martinez and Garcia, 2007a, 2007b; Tafarodi et al., 2010), locus of control orientation and self-concept (Mcclun and Merrell, 1998), externalizing and internalizing behavior, work orientation, sexual experience, and pregnancy history (Pittman and Chase-Lansdale, 2001), self-reliance, anxiety and depression (Steinberg et al., 1991), and personality and adjustment (Weiss and Schwarz, 1996).

Apparently the literature is replete with studies focusing on the direct/immediate impact of parenting style. But whether the impact of parenting style persists in the long-run to determine adulthood events including labor market outcomes remains an unexplored issue to date. Particularly, the literature as a whole is suggestive of significant relation between parenting style and children's academic outcomes and mental health. Although the causal link between the former and children's adult labor market outcomes seems unclear, it is left empirically untested so far.

Parenting style may affect children's adult labor market outcomes through several pathways. The first and most important pathway is academic performance. Parenting style is almost unanimously reported in the literature to significantly affect children's academic attainment (see Spera, 2005). It is empirically evident that children with better academic success in turn achieve better adult labor market outcomes (see Card, 1999).

The second important pathway is mental health. As mentioned above, many studies suggest that different aspects of mental health are heavily influenced by parenting style. The status of mental health in turn inevitably conditions children's labor market outcomes in adulthood. Balsa (2008) rightly notes "Mental health problems are likely to persist in adulthood and affects productivity. Depression and other health conditions may decrease labor force participation, reduce attendance to work for those employed, and affect productivity and wages".

Finally, physical health condition can mediate the impact of parenting style on children's adult labor market outcomes. As Kremers et al. (2003), Arredondo et al. (2006) and studies (e.g. Coombs and Landsverk, 1988) focusing on the impact of parenting style on substance use suggest, how parents rear their children may be an important determinant of the children's physical health condition. Children with better physical health condition are likely to show better labor market performance in their adulthood. Findings of several studies (e.g. Smith, 2009; Contoyannis and Dooley, 2010; Hass et al., 2011) imply that poor childhood health leads to worst adult labor market outcomes.

The aim of the present study is to explore the effects that different parenting styles have on children's adult labor market outcomes. Our hypotheses are the following: parenting style has lasting impact on children in terms of labor market success, and children reared with authoritative parenting style will have better position in labor market than those reared with other types of parenting style.

3 Data

3.1 The NLSY97

The NLSY97 is an extensive survey conducted on a nationally representative sample of American youths who were 12 to 16 years old in 1997. The sample consists of 4,599 males and 4,385 females of different racial backgrounds. The cohort was first interviewed in 1997 and continued to be interviewed each year since then. The survey covers a considerable number of variables pertaining to different labor market characteristics as well as many other aspects of human life including education, family background, and wealth status.

3.2 Variables

Four measures of labor market outcomes, namely, hourly real wages, number of weeks worked, number of weeks unemployed, and probability of having white collar job are used in my analysis. For calculating hourly real wages, I first divide total annual income received as wages and salary from all jobs by corresponding year's total annual hours worked at all jobs. Then I top-code them to $1000 and bottom-code to $1 in order to reduce bias from outliers. The NLSY reports annual income in nominal terms. Hence, the computed hourly wages are in nominal terms. To make real, I convert the recoded hourly nominal wages into 2000 constant Dollar using urban consumer price index (UCPI). Number of weeks worked is defined as the total number of weeks a respondent worked at any job during a year. Number of weeks unemployed refers to the total number of weeks a respondent remained unemployed during a year. On the other hand, probability of having white collar job is represented by a dummy variable which corresponds to only employed respondents. The dummy assumes a value of 1 if an employed respondent works in a white collar job and 0 otherwise.

Following Balsa (2008), I take averages of the first three of the above measures of outcomes, namely hourly real wages, number of weeks unemployed, and number of weeks worked. Then following convention, I take natural logarithm of the average hourly real wages. So my first three dependent variables are natural logarithm of average hourly real wages (henceforth log real wage), average number of weeks unemployed (henceforth weeks unemployed), and average number of weeks worked (henceforth weeks worked). Averages are taken across the latest three rounds of interview.[2] Balsa states three advantages of using average measures of outcomes- minimizing measurement error and the incidents of exogenous temporary shocks on labor market outcomes, mitigating problems of missing observations, and avoiding the problem of not observing a reservation wage. My fourth dependent variable is the above mentioned dummy for white collar job corresponding to the year 2010.

[2] Based on the availability of data, for log real wage, average was taken across 2007-2009 time period, and for weeks unemployed and weeks worked, averages were taken across 2008-2010 time period.

My key explanatory variable is parenting style. The NLSY97 asked respondents about the demandingness and responsiveness of their residential and nonresidential parents in rounds 1-4. Keeping consistency with the classification scheme mentioned in Figure 1, it created four categories of parenting style for each parent combining these two measures. These are authoritative parenting style (henceforth AVPS), authoritarian parenting style (henceforth ANPS), permissive parenting style (henceforth PPS), and uninvolved parenting style (henceforth UPS), which are coded 4, 3, 2, and 1, respectively (NLSY97 Codebook Supplement, Appendix 9). Because the influences of residential parents are understandably much more prominent than those of nonresidential parents, I consider only the parenting style of residential parents. Four rounds of observations on two residential parents give rise to eight values of parenting style for each respondent. It is important to note here that the necessity of distinguishing between residential and non-residential parents arises because in advanced societies like the US it often happens that for different reasons children may get detached from biological parents and stay under the direct guardianship of persons other than biological parents. Given the nature of my study, what matters is residential relationship rather than biological one. In other words, it is residential parents who are in the best position to influence children no matter those parents are biological or not.

I construct parenting style variable for this analysis considering eight observations for each respondent. First, I determine the parenting environment under which a respondent grew up for each year combining both parents' parenting styles in the corresponding year**.** If any parent is absent, his or her parenting style is assumed to be ‘uninvolved’. On the demandingness dimension, parenting environment is identified as demanding if at least one parent has demandingness. On the responsiveness dimension, parenting environment is identified as responsive if at least one parent has responsiveness. Table 1 illustrates the determination of parenting environment.

Having determined parenting environment by year, I consider a parenting environment an index of parenting style if a respondent experienced that parenting environment most of the years. That means the parenting style variable amounts to mode parenting style across the years in which parenting style is reported. Since the NLSY97 has data on parenting style for four rounds, there is a chance of bimodal situation (2 vs. 2). In that case, I take mode parenting style across the first three years as the best possible approximation. The reason is that the impacts of earlier years’ parenting styles are likely to be more prominent than those of later years’ parenting styles. Table 2 is an illustration of the determination of parenting style.

Understandably, respondents experiencing different types of parenting style are different in many observed and unobserved ways. These differences need to be controlled in order to obtain unbiased estimates. In an effort to control for observed heterogeneity, I use a number of demographic and family background variables. Demographic variables include age and dummies for race and gender.[3] Family background is characterized by family size, parents’ education, and household net worth. Since ability of a respondent may simultaneously influence parenting style and outcome variables and there is no direct measure of ability, I use the Peabody Individual Achievement Test (PIAT)

[3] Age variable is constructed by taking average of age across the period (1997-2000) in which parenting style is reported.

percentile score in 1997 as a proxy of ability. Although obviously PIAT is also influenced by parenting style, this is less of an issue in this study because most of parenting style data comes from the years after 1997. To check whether the effects of parenting style, if there is any, are mediated by education and health, I use highest grade competed and health status as controls in a different scheme of regressions.

3.3 Sample

I exclude the observations that have missing values for any variable under consideration. However, if parenting style variable is missing due to valid skip I replace it by 1 which means uninvolved parenting style. The reason for doing this is that valid skip in this case implies absence of corresponding parental figure. The absence of a parenting figure may be thought of as equivalent to uninvolved parenting. The above exclusion criteria yield samples of 3061 and 2891 observations when outcome variables are 'log real wage' and 'white collar job', respectively. On the other hand, the sample size is found to be of 3719 observations for both the remaining outcome variables, namely 'weeks unemployed' and 'weeks worked'.

3.4 Summary Statistics

Because samples used in this study are almost identical, presenting summary statistics for only one sample should be adequate. I decide to use the sample involved in my wage model for this purpose. However, summary statistics for the dependent variables of other three models are also included in order to have a greater picture. Table 3 displays the summary statistics. For brevity, only sample means are presented. Differences in sample means between different treatment groups are provided in Table 4.

The unconditional means of dependent variables suggest significant benefits of PPS and AVPS in terms of children's adult labor market outcomes. Particularly, children reared with AVPS seem to earn 8% more, remain unemployed 1.53 weeks less, work 4.92 weeks more, and be 8.3 percentage points more likely to find white collar job compared to children reared with UPS. Although children reared with PPS and children reared with UPS are predicted be the same in terms of earnings and the likelihood of being in white collar job, the former remain unemployed 0.95 weeks less, and work 3.2 weeks more compared to the latter. Children reared with ANPS, on the other hand, are found no different than those reared with UPS in labor market performance. The superiority of AVPS over PPS and ANPS is also apparent. Children with the experience of AVPS are expected to remain unemployed 0.58 weeks less and work 1.73 weeks more than those with the experience of PPS. Relative to children with the experience of ANPS, they earn 8.5% more, stay unemployed 0.70 weeks less, and work 2.80 weeks more. For more visualization, sample means of outcome variables are presented through a bar chart in Figure 2.

It is evident from the remainder of the summary statistics is that in most of the cases the four treatment groups are significantly different from each other in control variables. Worth mentioning is the case of AVPS. Children reared with AVPS are significantly different from children reared with UPS in all controls except white dummy and household size. They are also significantly different from those who experienced ANPS in all controls except black dummy, age, and household size. However, the case is less so when this group is compared with children having experience of PPS.

The most important pattern that the summary statistics reveals is that as a whole, children having experience of AVPS have the best labor market performance among the treatment groups as I hypothesize. Children having experience of ANPS are found no different than children having experience of UPS and PPS. Children raised PPS are found to be better than children raised with UPS in two labor market outcomes, namely weeks unemployed and weeks worked. However, since these predictions are drawn from unconditional means, they do not confirm any causal effects of parenting style on labor market performance. To see if these effects are causal, I estimate the relationship between parenting style and labor market outcomes in a regression framework, which will be discussed in the next section.

4 Empirical Strategies

Each of my outcome variables is modeled as a function of parenting style and other covariates. There are four groups of respondent corresponding to UPS, PPS, ANPS, and AVPS, respectively. I construct three dummy variables for the last three groups and use them in my models as representative of parenting style. The first group is used as the reference group. Accordingly, the equation to be estimated is of the form:

$$y_i = \gamma_1 p_{1i} + \gamma_2 p_{2i} + \gamma_3 p_{3i} + \boldsymbol{\beta x_i} + \varepsilon_i \tag{1}$$

where y_i is a labor market outcome; p_{1i}, p_{2i}, and p_{3i} are dummies for being reared with PPS, ANPS, and AVPS, respectively; $\boldsymbol{x_i}$ is a vector of other covariates; ε_{it} is the error term; and γ_1, γ_2, γ_3 and $\boldsymbol{\beta}$ are the parameters to be estimated. I focus on the estimation of γ_1, γ_2, and γ_2, because they are used to measure the effects of parenting style on labor market outcomes.

The equation is estimated using ordinary least squares (OLS) when the outcome variable is either log real wage, or weeks unemployed, or weeks worked. On the other hand, logit regression is used when the outcome variable is a dummy for white collar job.

As the first attempt, I estimate the models letting the vector $\boldsymbol{x_i}$ contain only demographic and family background variables. This attempt addresses the problem of heterogeneity in observed variables. It is important to note that reverse causality, a significant source of endogeneity, is completely absent in my models because parenting style and labor market outcomes are measured in very different times. Nevertheless, endogeneity is likely to remain a threat due to unobserved ability. Children's ability is most likely to influence parents' decision about how they will rear their children and at the same time it affects future labor market outcomes. That is why in the next attempt, I re-estimate the models controlling for the PIAT percentile score, which is considered to be a proxy measure of unobserved ability. It needs to be mentioned that PIAT is influenced by many background variables including parents' smoking behavior (Batty et al., 2006), parents' cognitive ability, parents' ethnicity, family structure (Wanstrom, 2007), family income, whether the children are from disadvantaged families (Dahl and Lochner, 2012), and childhood malnutrition (Averett and Stifel, 2007), and hence can be seen as the stock of human capital up until the time the test was conducted. Therefore, controlling for this variable in my setup amounts to controlling for many confounding variables during the time until 1997. Figure 3 clarifies the point.

As pointed out earlier, the apparent causal effects, if there is any, of parenting style on adult labor market outcomes may be mediated through three main channels, namely mental development, education, and health. To see if the premise is true, I further estimate the models cumulatively adding highest grade completed and health status as controls. Since there is no usable psychological data in the NLSY97, the claim about the mediation through mental development cannot be tested. If mediation by education and health is found, it will mean that intervention programs that facilitate education and health would be effective in mitigating the negative impact, if there is any, of parenting style on labor market outcomes.

Finally, children's intensive attachment to mothers may provoke someone to argue that mother's parenting style is much more relevant than father's. This point is substantiated by the fact that in her seminal research, Baumrind favors the mother's parenting style when it differs from the father's (see Weiss and Schwarz, 1996). Therefore, responding to the above claim, I redo all of the above estimations considering parenting style of residential mother only.

5 Empirical Results

5.1 Key Results

Main results are summarized in Table 5. For brevity, only the effects of key explanatory variables are reported. Columns 1, 3, 5, and 7 reports results from preliminary estimations in which only demographic and family background variables are controlled for. These results may be plagued by endogeneity arising from unobserved ability. To mitigate this problem, I modify the estimations to account for unobserved ability using the PIAT percentile score as control. Results from these estimations are presented in columns 2, 4, 6, and 8.

Columns 1 and 2, which contain estimates from log real wage equations, suggest that irrespective of whether unobserved ability is controlled or not parenting style does not have any impact on wages whatsoever. However, although statistically insignificant, the estimates appear to reduce substantially once unobserved ability is controlled.

Estimates from equations for weeks unemployed are reported in columns 3 and 4. These estimates reveal that if unobserved ability is left unaccounted, children reared with PPS and AVPS are found to remain less unemployed than children reared with UPS by 0.89 and 1.46 weeks, respectively. ANPS is found to have no statistically significant effects. The estimates undergo considerable changes when unobserved ability is accounted for. For example, each of the three key coefficients reduces in absolute magnitude, and permissive parenting style becomes insignificant. AVPS, however, remains statistically significant at the 1% level of significance. In particular, children reared with AVPS are now found to be less employed than children with UPS by 1.3 weeks. The condition of ANPS in terms of statistical significance is also left unchanged.

Columns 5 and 6 provide estimates from equations for weeks worked. It is evident from these estimates that regardless of specifications (with and without having unobserved ability controlled for), relative to UPS, both PPS and AVPS have significant impact on weeks worked with the later having larger impact than the former, while ANPS seems to be immaterial. Specifically, after controlling for unobserved ability, children having experiences of PPS and AVPS are predicted to work more than those having experience of UPS by 2.4 and 4.03 weeks, respectively. These effects are even larger when unobserved ability remains unaccounted for.

Finally, estimates from equations for white collar job are presented in columns 7 and 8. In terms of statistical significance, the estimates are qualitatively the same across models with and without having unobserved ability controlled- only AVPS affects the probability of getting a white collar job. However, the estimates undergo a quantitative reduction when unobserved ability is accounted for. Children with the experience of AVPS are expected to have a 7.4 percentage points higher probability of holding a white collar job compared to children with the experience of UPS when unobserved ability is not controlled for. This figure goes down to 5.7 percentage points after controlling for the unobserved ability.

A common pattern observed from the above estimations is that controlling for unobserved ability results in the reduction of estimates (absolute magnitude), implying the presence of endogeneity due to omitted ability variable. This justifies the statement that unobserved ability influences parents' decision about parenting style and labor market outcomes simultaneously, and hence justifies the use of PIAT as one of the controls to isolate the causal effects of parenting style.

5.2 Are the Effects Mediated by Education and Health?

Having examined key results, I go for testing whether the significant effects found above are mediated by educational attainment and health status as has been claimed earlier. I exclude the model for log real wage from this test because no effects of parenting style on wages are evident from the above estimations. For the remaining models, I sequentially add highest grade completed and health status to the models as controls. Due to lack of usable psychological variables in the NLSY97, I am unable to test the possibility that mental development can play role as a mediator.

Table 6 summarizes the results. Columns 2, 5, and 8 reports estimates from equations in which only highest grade completed is added, while estimates resulting from adding both highest grade completed and health status appear in columns 3, 6, and 9. On the other hand, respective estimates from Table 3 that result from controlling unobserved ability are put in columns 1, 4, and 7 for making comparison convenient.

Estimates contained in columns 1, 2, and 3 provide evidence of gradual decline in the absolute values of the effects of parenting style on weeks unemployed due to the successive inclusion of highest grade completed and health status as controls. The effect of AVPS, the only significant effect in this case, goes down to -0.9 once highest grade completed is added. It further deteriorates to reach -0.81 following the inclusion of health status.

As for weeks worked, what follow the gradual inclusion of highest grade completed and health status are qualitatively the same as those happened in the case of weeks unemployed. Importantly, as evident from columns 4, 5, and 6, PPS turns out to be statistically insignificant when educational attainment is controlled for. It remains insignificant when health status is also controlled for. AVPS, however, remains significant in all specifications, although the magnitude of the effect decreases gradually. After controlling for highest grade completed and health status, children reared with AVPS are predicted to work more than those reared with UPS by 2.13 weeks. This figure is 4.03 when highest grade completed and health status are not controlled.

Finally, estimates from the model for white collar job undergo a little bit different consequences of controlling for highest grade completed and health status than the above in terms of magnitude. As demonstrated in columns 7, 8, and 9, although the absolute magnitudes of the three effects drastically decline following the inclusion of highest grade completed, they remain the same or have a little increase when both highest grade completed and health status are included. As for statistical significance, AVPS, the only significant variable in this model, turns insignificant when highest grade completed is controlled and remains insignificant when both highest grade completed and health status are controlled.

From the above analysis of Table 6, two points stand out. In the link between parenting style and adult labor market outcomes, the mediation of education and health factors are clearly evident, which is reflected in the gradual decline in absolute magnitude of the effects as well as in the fact that the effects which was previously significant become statistically insignificant or less significant as a result of controlling highest grade completed and health status. Secondly, that after controlling education and health, the effect of AVPS still remains significant in the cases of weeks unemployed and weeks worked suggest that these two outcomes are affected through channels other than education and health including mental development. Probability of holding a white collar job seems to be affected by AVPS solely through education and health.

5.3 Results when Only Mother's Parenting Style is Taken into Consideration

Results contained in Tables 5 and 6 are reproduced in Tables 7 and 8 taking only mother's parenting style into consideration. According to Table 7, the results remain qualitatively the same in terms of the directions of the effects. The statistical significance of the effects also remain the same except ANPS, which was found insignificant in the estimations of white collar job equations, now turns out to be predictive of having white collar job. The results, however, undergoes slight changes in magnitude. As for Table 8, a few changes take place. AVPS is no more significant in predicting weeks unemployed. Besides, the effect of AVPS on weeks worked slightly increases in magnitude.

In sum, no matter both parents' parenting styles or only mother's parenting style are considered, results convey virtually the same message- AVPS is the best among parenting styles in terms of the effects on labor market outcomes, and education and health are proved to be among channels through which those effects pass.

6 Discussion

As suggested by Table 5, ANPS is found to be as good as UPS across all labor market outcomes. PPS appears to be better than UPS only for weeks worked. For other outcomes, it is as good as UPS. Most impressive finding is about AVPS. As I hypothesized, this parenting style turns out to be the best among all parenting styles for all outcomes except log real wage. In fact, for log real wage, parenting style seems immaterial.

The fact that my hypothesis passes empirical test substantiates the point that neither parents' supportiveness without demandingness nor parents' demandingness without supportiveness yields better outcomes for children than parents' noninvolvement in children's matters. Supportiveness and demandingness complement each other to make synergistic effects on a range of children's outcomes. In the literature, numerous studies, as I discussed in literature review, show the importance of parenting style to a child's development in terms of education, health, and psychological strength. My findings are quite in line with those studies.

7 Summary and Conclusion

The available literature on parenting style utterly lacks studies focusing on the long-run effects of parenting style including the effects on children's adult labor market outcomes. In this study, using the NLSY97, a nationally representative dataset of the US, I seek to mitigate this lack by empirically examine the existence and the strength of the causal link between how parents rear their children and children's labor market outcomes in their adulthood. I also investigate whether the link, if there is any, is mediated by education and health. The mediation through mental development could not be tested due to unavailability of suitable data.

I use demographic and family background variables to control for observed heterogeneity. Considering the possibility that ability of a child, which is unobserved, may simultaneously determine parents' child rearing style and the child's adult labor market outcomes, I include the PIAT percentile score, a surrogate for unobserved ability, in my control variables to reduce endogeneity. To see the role of education and health in mediating the influence of parenting style, I re-estimate my models cumulatively including highest grade completed and health status as controls.

My findings provide evidence of parenting style being a determinant of children's adult labor market outcomes. Importantly, AVPS is found to be the most beneficial to children. More specifically, on average, children with the experience of AVPS is predicted to remain less unemployed by 1.3 weeks, work more by 4.03 weeks, and be 5.7 percentage points more likely to have white collar job compared to children with the experience of UPS. PPS, however, is seen to be better than UPS only in terms of weeks worked. It raises the number of weeks worked by 2.4 in relation to UPS. In terms of other labor market outcomes, it is no different than UPS. ANPS, on the other hand, seems to remain as good as uninvolved parenting style across the series of estimations performed. Regarding the mediating factors, findings clearly suggest that educational and health mediate the influences of parenting style.

The above findings have important policy implications in the context of decaying family values and problematic employment situation that the US is experiencing nowadays. Relevant authorities must take the benefits of authoritative parenting style and the costs of non-authoritative parenting style into account during enactment of policies for family affairs especially those involving parent education and training. Intervention through education/health is a feasible option. Also, it should be kept in mind that difficulties in terms of labor market outcomes can be partially mitigated by implementing policies that promote authoritative approach to parenting.

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TABLES AND FIGURES

Table 1: Determination of parenting environment

Dimension	Father (Authoritative)	+	Mother (Permissive)	=	Situation as a whole	Parenting environment
Demandingness	Demanding	+	Non-demanding	=	Demanding	Authoritative
Responsiveness	Responsive	+	Responsive	=	Responsive	

Table 2: Determination of parenting style

Year 1	Year 2	Year 3	Year 4	Mode parenting style	Parenting style index
Permissive	Authoritative	Authoritative	Authoritative	Authoritative	Authoritative
Permissive	Authoritative	Permissive	Authoritative	Permissive (bimodal situation)	Permissive (mode across the first three years)

Table 3: Sample means of variables for full sample and subsamples[a]

Variables	Full sample	UP	PP	ANP	AVP
Dependent variables					
Logarithm of real wage	2.266	2.214	2.247	2.209	2.294
Weeks unemployed	4.080	5.244	4.291	4.412	3.715
Weeks worked	35.359	32.152	35.339	34.262	37.066
Dummy for white collar job	0.516	0.453	0.496	0.515	0.536
Demographic variables					
Dummy for white	0.549	0.537	0.589	0.472	0.549
Dummy for black	0.234	0.191	0.216	0.267	0.242
Dummy for Hispanic	0.208	0.256	0.189	0.250	0.201
Dummy for male	0.521	0.463	0.522	0.469	0.541
Age	15.117	15.224	15.284	15.037	15.037
Family background variables					
Household net-worth	89293.600	56512.810	86405.260	69583.610	99744.200
Household size	4.397	4.359	4.149	4.509	4.499
Residential parents' education	12.571	11.947	12.609	12.267	12.710
Innate ability					
PIAT	49.151	39.821	47.559	45.179	52.151
Other controls					
Highest grade completed	13.345	12.056	13.197	12.974	13.688
Health status	2.236	2.508	2.176	2.436	2.183
N	3061	246	805	352	1658

[a] Four subsamples correspond to UP (uninvolved parents), PP (permissive parents), ANP (authoritarian parents), and AVP (authoritative parents), respectively
* Significant at the 10% level ** Significant at the 5% level *** Significant at the 1% level

Table 4: Differences in sample means of variables between subsamples[a]

Variables	UP vs. PP	UP vs. ANP	UP vs. AVP	PP vs. ANP	PP vs. AVP	ANP vs. AVP
Dependent variables						
Logarithm of real wage	0.033	-0.004	0.080*	-0.038	0.047	0.085**
Weeks unemployed	-0.953*	-0.832	-1.529***	0.121	-0.576**	-0.697*
Weeks worked	3.197**	2.120	4.924***	-1.077	1.727***	2.804***
Dummy for white collar job	0.043	0.0618	0.083**	0.019	0.040*	0.021
Demographic variables						
Dummy for white	0.052	-0.065	0.012	-0.117***	-0.040*	0.077***
Dummy for black	0.025	0.076**	0.051*	0.051*	0.026	-0.025
Dummy for Hispanic	-0.067**	-0.006	-0.055**	0.061**	0.013	-0.049**
Dummy for male	0.058	0.005	0.078**	-0.053*	0.012	0.072**
Age	0.060	-0.187**	-0.186**	-0.247***	-0.246***	0.000
Family background variables						
Household net-worth	29892.450***	13070.800	43231.380***	-16821.650**	13338.930**	30160.580***
Household size	-0.210**	0.151	0.140	0.361***	0.350***	-0.010
Residential parents' education	0.662***	0.320	0.763***	-0.342*	0.101	0.443**
Innate ability						
PIAT	7.738***	5.358*	12.330***	-2.380	4.592***	6.972***
Other controls						
Highest grade completed	1.141***	0.918***	1.632***	-0.223	0.491***	0.713***
Health status	-0.332***	-0.073	-0.325***	0.260***	0.007	-0.253***

[a] Four subsamples correspond to UP (uninvolved parents), PP (permissive parents), ANP (authoritarian parents), and AVP (authoritative parents), respectively.
* Significant at the 10% level ** Significant at the 5% level *** Significant at the 1% level

Table 5: Results from OLS and logit estimations[a]

	Log real wage		Weeks unemployed		Weeks worked		White collar job	
	1	2	3	4	5	6	7	8
Dummy for PPS	-0.0005 (0.050)	-0.019 (0.049)	-0.889* (0.521)	-0.816 (0.514)	2.560** (1.157)	2.398** (1.154)	0.038 (0.035)	0.029 (0.035)
Dummy for ANPS	0.004 (0.060)	-0.015 (0.060)	-0.871 (0.599)	-0.799 (0.594)	2.149 (1.322)	1.989 (1.318)	0.051 (0.040)	0.044 (0.040)
Dummy for AVPS	0.048 (0.047)	0.013 (0.046)	-1.457*** (0.491)	-1.295*** (0.485)	4.387*** (1.094)	4.025*** (1.095)	0.074** (0.033)	0.057* (0.033)
Control for PIAT?	×	✓	×	✓	×	✓	×	✓
N	3061	3061	3719	3719	3719	3719	2891	2891

[a] For log wage equations, reported are the percentage changes (when multiplied by 100) in wage due to change in treatment status from uninvolved parenting style to other categories. In the case of equations for white collar job, marginal effects are reported. For other equations, coefficients are reported. Figures in parentheses are robust standard errors. Logit estimations are performed for white collar job equations, while OLS estimations are performed for other equations.

*Significant at the 10% level ** Significant at the 5% level *** Significant at the 1% level

Table 6: OLS and logit results after controlling for education and health[a]

	Weeks unemployed			Weeks worked			White collar job		
	1	2	3	4	5	6	7	8	9
Dummy for PPS	-0.816 (0.514)	-0.542 (0.512)	-0.399 (0.514)	2.398** (1.154)	1.204 (1.130)	0.928 (1.131)	0.029 (0.035)	-0.014 (0.033)	-0.014 (0.033)
Dummy for ANPS	-0.799 (0.594)	-0.536 (0.592)	-0.529 (0.593)	1.989 (1.318)	0.842 (1.289)	0.829 (1.288)	0.044 (0.040)	-0.004 (0.038)	-0.005 (0.038)
Dummy for AVPS	-1.295*** (0.485)	-0.901* (0.485)	-0.805* (0.487)	4.025*** (1.095)	2.312** (1.080)	2.125** (1.081)	0.057* (0.033)	-0.010 (0.032)	-0.010 (0.032)
Control for education?	×	✓	✓	×	✓	✓	×	✓	✓
Control for health?	×	×	✓	×	×	✓	×	×	✓
N	3719	3719	3719	3719	3719	3719	2891	2891	2891

[a] In the case of equations for white collar job, marginal effects are reported. For other equations, coefficients are reported. Figures in parentheses are robust standard errors. Logit estimations are performed for white collar job equations, while OLS estimations are performed for other equations.

*Significant at the 10% level ** Significant at the 5% level *** Significant at the 1% level

Table 7: Results from OLS and logit estimations (only mother's parenting style considered)[a]

	Log real wage		Weeks unemployed		Weeks worked		White collar job	
	1	2	3	4	5	6	7	8
Dummy for PPS	0.020 (0.042)	-0.002 (0.041)	-0.758* (0.422)	-0.646 (0.419)	3.052*** (0.966)	2.804*** (0.967)	0.060** (0.030)	0.046 (0.029)
Dummy for ANPS	0.024 (0.054)	-0.005 (0.053)	-0.879* (0.516)	-0.747 (0.514)	2.131* (1.176)	1.837 (1.177)	0.095*** (0.036)	0.077** (0.036)
Dummy for AVPS	0.045 (0.041)	0.011 (0.041)	-1.067*** (0.415)	-0.910** (0.412)	4.242*** (0.948)	3.894*** (0.952)	0.100*** (0.029)	0.080*** (0.029)
Control for PIAT?	×	✓	×	✓	×	✓	×	✓
N	2973	2973	3621	3621	3621	3621	2808	2808

[a] For log wage equations, reported are the percentage changes (when multiplied by 100) in wage due to change in treatment status from uninvolved parenting style to other categories. In the case of equations for white collar job, marginal effects are reported. For other equations, coefficients are reported. Figures in parentheses are robust standard errors. Logit estimations are performed for white collar job equations, while OLS estimations are performed for other equations.

*Significant at the 10% level ** Significant at the 5% level *** Significant at the 1% level

Table 8: OLS and logit results after controlling for education and health (only mother's parenting style considered)[a]

	Weeks unemployed			Weeks worked			White collar job		
	1	2	3	4	5	6	7	8	9
Dummy for PPS	-0.646 (0.419)	-0.389 (0.417)	-0.290 (0.419)	2.804*** (0.967)	1.668* (0.950)	1.481 (0.953)	0.046 (0.029)	0.005 (0.029)	0.004 (0.029)
Dummy for ANPS	-0.747 (0.514)	-0.531 (0.512)	-0.530 (0.511)	1.837 (1.177)	0.885 (1.158)	0.882 (1.157)	0.077** (0.036)	0.041 (0.035)	0.041 (0.035)
Dummy for AVPS	-0.910** (0.412)	-0.572 (0.413)	-0.494 (0.414)	3.894*** (0.952)	2.398** (0.942)	2.250** (0.944)	0.080*** (0.029)	0.025 (0.028)	0.024 (0.028)
Control for education?	×	✓	✓	×	✓	✓	×	✓	✓
Control for health?	×	×	✓	×	×	✓	×	×	✓
N	3621	3621	3621	3621	3621	3621	2808	2808	2808

[a] In the case of equations for white collar job, marginal effects are reported. For other equations, coefficients are reported. Figures in parentheses are robust standard errors. Logit estimations are performed for white collar job equations, while OLS estimations are performed for other equations.

*Significant at the 10% level ** Significant at the 5% level *** Significant at the 1% level

	High in responsiveness	Low in responsiveness
High in demandingness	Authoritative parenting style	Authoritarian parenting style
Low in demandingness	Permissive parenting style	Uninvolved parenting style

Figure 1: A two-dimensional classification of parenting styles

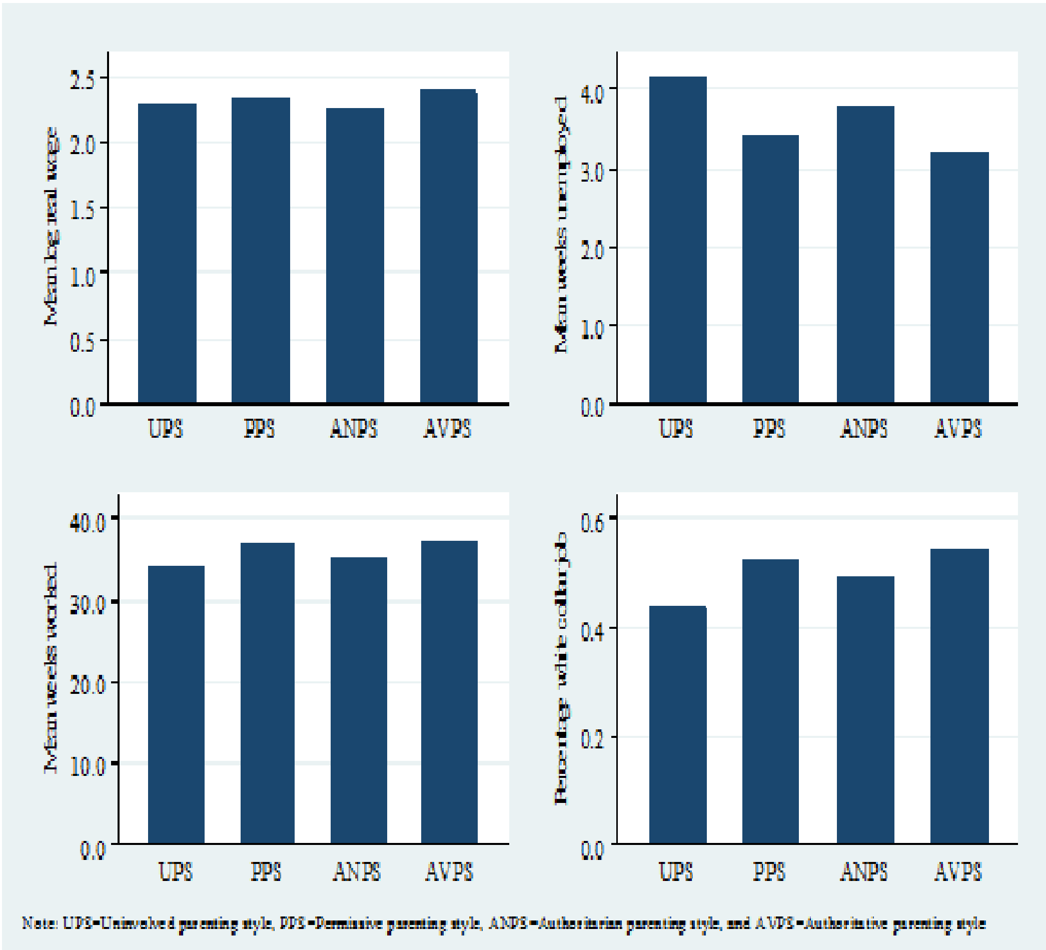

Figure 2: Parenting styles and labor market outcomes

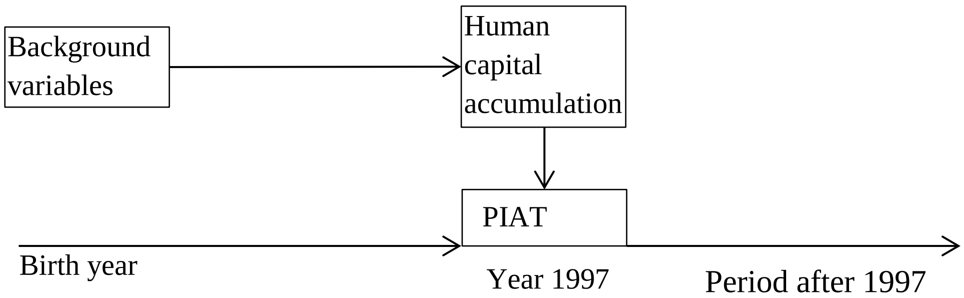

Figure 3: Use of PIAT score to mitigate unobserved heterogeneity

CHAPTER III

Does Obesity Matter for Wages? Evidence from the United States

1 Introduction

Obesity has become an issue of overwhelming concern around the world as well as in the United States (US) due to its unfavorable economic and social consequences. Global incidence of obesity has already more than doubled since 1980 (WHO, 2012). The US, like many other countries in the developed world, has had a similar experience. The percentage of obese adults in this country has almost tripled since 1980. There have been a major increase in obesity during the late 1980s followed by a gradual trend (Chou et al., 2004).[1] Adult obesity increased from 13.95% in 1976-1980 to as high as 35.70% in 2009-2010, while the figure remained in the vicinity of 13% in the 1960s and 1970s. Average body mass index (BMI), however, rose at a relatively moderate pace from 24.91 in 1959-1962 to 28.70 in 2009-2010 (See Chou et al., 2004 and Ogden et al. 2012). According to a National Center for Health Statistics (NCHS) data brief, around 35.7% of adults and 16.9% of children and adolescents in the US were obese in 2009-2010.

The consequences of obesity in terms of both public and private costs are perceived to be substantial (see Cawley and Meyerhoefer, 2012; Wolf and Colditz, 1998; Thompson *et al.*, 1998). As it is seen, obesity may give rise to three types of economic

[1] According to World Health Organization's (WHO) definition, one is categorized as obese if BMI ≥ 30, overweight if $30 > \text{BMI} \geq 25$, healthy weight if $25 > \text{BMI} \geq 18.5$, and underweight if BMI < 18.5. BMI or body mass index is defined as weight in kilogram divided by height in meter squared. (source: http://apps.who.int/bmi/index.jsp?introPage=intro_3.html, Accessed on 9 June 2012)

costs. First, it contributes to social loss by increasing national health care expenditures and inducing the loss of potential gross domestic product (GDP). Cawley and Meyerhoefer (2012) estimated obesity-induced increases in annual medical costs at around $2,741 (in 2005 dollars). They also estimated the cost of treating obesity among the US adult non-institutionalized population at $190.2 billion, which was equivalent to 20.6% of national spending on medical care. The loss of potential GDP, on the other hand, occurs as a result of absenteeism and lower productivity. Using the 1994 National Health Interview Service (NHIS) data, Wolf and Colditz (1998) showed that the number of lost work-days associated with obesity was 39.2 million, which amounted to $3.9 billion (in 1995 Dollar). Besides, 239 million restricted-activity days, 89.5 million bed-days, and 62.6 million physician visits contributed to the loss of potential GDP.

Second, employers of obese workers have to spend more in the form of insurance and other costs. Thompson *et al.* (1998) reported that the annual economic costs of obesity to business in the US in 1994 for insurance, paid sick leave, and other payments amounted to $12.7 billion, which was equivalent to 0.17% of GDP.

Finally, an obese person himself may be subject to wage penalty. Under certain assumptions, the marginal productivity theory of wages predicts that wages are determined by workers' productivity. The productivity of labor in turn seems to be affected by health and body weight. For example, an obese worker may become less productive due to obesity-induced health barriers and myopic attitudes toward the future. As a result, the wage of an obese worker tends to be lower. Moreover, employers and consumers discrimination may result into lower wages for obese workers (Baum and

Ford, 2004). Employers tend to have aversion to obese workers out of the perception that customers may experience discomfort while interacting with the obese. Besides, employers are aware of the increased cost resulting from recruiting obese workers due to their poor performance in the workplace as well as the health care provisions they deserve.

In view of the above scenario, policy intervention seems necessary to raise consciousness among consumers as well as among food producers with regard to healthier choices. This study attempts to contribute in policy design by providing empirical facts about how obesity affects wages, if at all. The analysis is done taking workers' gender and ethnic backgrounds into consideration. Different econometric estimation methods are applied using National Longitudinal Survey of Youth 1997 (NLSY97) data to identify causality between obesity and wages.

The remainder of this paper is outlined as follows. Section 2 reviews existing literature. Section 3 presents a discussion on data used in this study. Strategies adopted are detailed in section 4. Findings are reported in Section5. An overall discussion of the findings is provided in Section 6. Section 7 contains summary and concluding remarks.

2 Literature Review

Most of the studies focused on gender effects without segregating genders by race and ethnicity. To the best of my knowledge, only three studies, namely, Averett and Korenman (1996), Cawley (2004), and Wada and Tekin (2007), so far modeled the impact of obesity on wages separately for different ethno-gender groups. In fact, ethnicity matters in terms of many psychological, socioeconomic and family background variables. The descriptive statistics summarized in Table 1 and Table 2 suggest that there are non-trivial systematic differences between ethnic groups. Inter-ethnic variations are wiped away once all ethnic groups are lumped together into a single group. Thus it is reasonable to cast doubt on the findings of studies that estimate only gender effects without extending the analyses toward ethnic dimension (Wada and Tekin, 2007).

Averett and Korenman (1996) estimated ordinary least squares (OLS) and sibling-difference models using a 1988 cross-section sample of 5,090 women and 4,951 men drawn from the National Longitudinal Survey of Youth 1979 (NLSY79). They found a statistically significant wage penalty for obese women and weak and mixed results for men in both of their models. Black women, however, were found to suffer no wage penalty for obesity. In an effort to circumvent the problem of reverse causality, they used seven-year lags of weight variables. Omitted variable bias remained partly unaddressed in their study. Using a pooled data from the NLSY79, Cawley (2004) examined the effects of obesity on wages by gender and ethnicity. His OLS estimates indicated that heavier females of all ethnic groups and heavier Hispanic males earned less than their lighter counterparts while heavier black males earned more. In order to eliminate time-invariant unobserved heterogeneity, he used a fixed-effects (FE) model and found that all coefficients except those of white females and black males lost significance. Finally, he estimated instrumental variable (IV) models using sibling's body weight as instrument to deal with time-varying unobserved heterogeneity. The findings of the IV estimates suggested that only white females suffered from wage penalty for obesity and all other ethno-gender groups neither suffered penalty nor received any premium for obesity. One problem of his study is that the models in which continuous measures of weight were used did not capture nonlinear effects of weight. Wada and Tekin (2007) followed the same procedure in modeling as that of Cawley (2004) with the exception that they tried to capture nonlinear effects of a continuous measure of weight by incorporating weight squared as an independent variable, and they estimated their main models using body fat (BF) and fat free mass (FFM) instead of BMI as measures of obesity. Findings from their BF- and FFM-based models implied that wages tended to decrease with BF and increase with FFM for whites regardless of gender. Wages of all other groups appeared unresponsive to either BF or FFM. They, however, additionally estimated BMI-based models. Results of those models indicated that wages initially increased and then decreased as BMI went up for black females and all groups of males. For white and Hispanic females, no effects of BMI were apparent. When BMI and BMI squared were replaced by weight categories (obese, overweight and underweight) in the regressions, heavier blacks regardless of gender were found to receive wage premium and heavier white females were found to suffer wage penalty. Coefficients for all other groups remained statistically insignificant.

Like Wada and Tekin (2007), Greeve (2008) also included BMI squared to capture nonlinearity of the effects of BMI. He adopted IV method as an identifying strategy to examine gender- and sector-specific (private/public) impacts of BMI. Both male and female workers in the private sector were found to suffer from significant wage penalty for higher BMI, while no impact for either males or females was evident in the public sector. Baum and Ford (2004) investigated gender effects using the NLSY79. They estimated individual-difference, sibling-difference, and individual-cum-sibling-difference models in addition to OLS to control for unobserved individual and family heterogeneities. Their OLS and individual-difference models provided evidence of statistically significant wage penalties for both men and women. The impact remained significant only for women when individual-cum-sibling-difference model was estimated. The sibling-difference model, however, provided no evidence of significant wage effects of obesity either for men or for women. Using pooled cross-sectional health survey data for 1997 and 1998, Morris (2006) looked into direct and indirect effects of BMI on occupational attainment for men and women in England. His OLS estimates suggested that BMI had a positive direct impact on men's wages and a negative direct impact on women's wages. In the case of indirect effects, the signs of the coefficients remained unchanged for females but showed considerable variation for males. Using IV, he found no significant impact either for men or for women. However, his OLS results were preferred because Hausman test failed to reject the null hypothesis of exogeneity of BMI. Han (2006) conducted a thorough investigation into the impact of obesity on labor market outcomes by gender, age groups and occupation types. Using the NLSY79, he estimated two-stage IV model after controlling for individual fixed-effects. One implication of his findings was that obesity lowered wages for females but the effects were of mixed pattern for males. Norton and Han (2007) used variables related to genetic information as instruments to tackle the endogeneity problem and found no impact of BMI on wages for either males or females.

The apparent shortcomings of the existing literature are twofold. First, most of the studies had an implied assumption that the effect of BMI is linear throughout, while actually this may not be the case. Imposing linearity in the relation between BMI and log of wage may be restrictive (Wada and Tekin, 2007). Second, most of the studies did not estimate the effects separately for different ethno-gender groups. As mentioned earlier, estimations based on an aggregated approach may give rise to artifacts. To the best of my knowledge, Wada and Tekin (2007) is the only study that attempted to address both of these issues. A shortcoming of this study is that nothing was done in its fixed-effects estimation to deal with the problem of simultaneity. It, however, used lag BMI in its OLS models to remediate this problem.

This study is an improvement on the current literature in that it deals with the above mentioned econometric issues in one framework. It estimates the effects of obesity separately for each of the six ethno-gender groups. It captures the nonlinearity of BMI effects by incorporating BMI squared as an independent variable. When categorical measures of weight are used, it introduces three binary variables (obese, overweight and underweight) instead of only one. Lagged BMI is used in its fixed-effects estimation to address the problem of simultaneity. Moreover, this is the first paper to draw sample from the NLSY97 in the literature of obesity-induced wage penalty.

3 Data

3.1 The NLSY97

The NLSY97 is an extensive survey conducted on a nationally representative sample of American youths who were 12 to 16 years old in 1997. The sample consisted of 8,984 respondents of whom 4,599 are male and 4,385 are female of different racial backgrounds. The cohort was first interviewed in 1997 and continued to be interviewed each year since then. The survey covers a wide range of variables predominantly associated with labor market behavior, educational background and demographic characteristics.

3.2 Sample

The following restrictions are imposed while selecting sample for this study. (i) Presumably the wages of young workers are highly variable because of their enrollment status (Averett and Korenman, 1996). People are generally engaged in building educational career in their younger ages. The younger a person is, the more likely he or she is to be enrolled in school. Keeping that in mind and following convention, respondents aged less than 18 are excluded. (ii) The NLSY97 records four categories of races: black, Hispanic, mixed, and non-black-non-Hispanic (henceforth white). The number of respondents of mixed category is only 83 compared with 2335 blacks, 1901 Hispanics and 4665 whites. Due to small number, observations for the mixed category are not as useful in estimation, so they are dropped. (iii) The respondents who are in military job are excluded because of the fact that labor market behaviors in military professions are not comparable to those in civil professions. (iv) Women face a situation of unusual weight gain during pregnancy. This weight gain is not supposed to affect wages in the same way as normal weight gain does. Thus pregnant respondents are dropped. (v) Finally, observations having missing values for any variable under consideration are excluded for the sake of analytical simplicity. The above exclusion criteria yield a pooled sample of 17,191 person-year observations. Female and male observations are respectively 8,408 and 8,783.

3.3 Variables

The dependent variable used in this study is natural logarithm of wage. The NLSY reports wages in nominal terms. They are top-coded to $1000 and bottom-coded to $1 in order to avoid the problems related to outliers. Since we are interested in the change in real wages, the recoded nominal wages are converted into 1982 constant Dollar by using urban consumer price index (UCPI) before taking the logarithm.

The key explanatory variable is body weight, which is measured in this study by the continuous variable BMI and binary variables obese, overweight, healthy weight, and underweight. BMI is used in some specifications, while obese, overweight, and underweight are used in others. Healthy weight is chosen as base category in the latter specifications and hence is not explicitly introduced as right hand side variable. BMI is calculated as weight in kilograms divided by height in meters squared. The binary variables are defined by BMI splines. One is said to be healthy weight if his or her BMI is equal to or above 18.5 and below 25. If one's BMI falls below 18.5, he or she is underweight. On the other hand, obese is defined as BMI equal to or above 30 and overweight is defined as BMI equal to or above 25 and below 30. Since height and weight in the NLSY are self-reported, those data are likely to have reporting error, which may in turn cause bias in coefficient estimates. To reduce that bias, self-reported height and weight are corrected for reporting error following a method suggested by Cawley (2004).[2]

In addition to body weight, a long list of variables is used as controls. Human capital variables, such as highest grade completed, job experience, job experience squared, tenure, and a dummy for enrollment status are used to control for heterogeneity in human capital. Demographic variables, such as age, a dummy for region, household size, the number of household members aged less than 18, the number of kids, a dummy for urban residence, and a dummy for US born are used to control for demographic differences. Respondents may differ in terms of family background. Keeping that in mind, I include parents' highest grade completed, a dummy for whether respondents lived with both biological parents in 1997, and household net-worth at age 20 as variables representing family background. Dummies for white-collar jobs and part-time jobs are included in order to control for employment characteristics. Since wages may differ across industries, dummies for sixteen industries are incorporated to control for those differences. It is also reasonable to argue that respondents are much different in psychological and behavioral aspects, which may affect both weight and wage. Thus I control for attitudinal variables; namely, a mental health index, a measure of how organised respondents are, conscientiousness, dependability, thoroughness, agreeability, a measure of how difficult respondents are, and trustfulness. Year dummies are incorporated to control for economy-wide changes, such as business cycles and trends in

[2] Estimated relations between true and self-reported values are used to predict the true values for weight and height in the NLSY97. The relations for different ethno-gender groups were separately estimated from the Third National Health and Nutrition Examination Survey (NHANES III) data. The coefficients characterizing the said relationships are taken from Cawley and Burkhauser (2006).

different macroeconomic indicators over the period of study. The score of the Armed Services Vocational Aptitude Battery (ASVAB) test is used as a proxy for unobserved ability. Besides, I include a measure of health condition (one year lag), a dummy for smoking, the number of cigarettes per day, a dummy for drinking, the number of drinks per day, a dummy for whether respondents ever used marijuana, and a dummy for whether they ever used cocaine.[3]

3.4 Summary Statistics

For brevity, only sample means are presented as summary statistics in Tables 1 and 2. Table 1 is for the female sample and Table 2 is for the male sample. These tables suggest that the percentage of obese is higher for females among whites and blacks. The percentage of underweight is higher for females and the percentage of overweight is higher for males regardless of ethnicity. The percentage with a healthy weight is higher for females among whites and Hispanics. Among blacks this percentage is higher for males. Females have higher average BMI among whites and blacks. The reverse is true for Hispanics. Males' wages are higher than females' wages regardless of ethnic identity. Tables 2 and 3 also show that neither healthy-weight males nor healthy-weight females earn the highest wage among workers of all weight categories.

Table 3 provides a detailed account of mean wages for workers of different weight categories against each of the ethno-gender groups. One noticeable implication of this table is that for none of the ethno-gender groups except Hispanic males, healthy weight is the category that earns the highest mean wage. Among Hispanic males, healthy-weight

[3] Health condition is measured on a scale of 5 with 1 being an indicator of excellent health and 5 being an indicator of poor health.

workers earn the highest average wage of \$6.66. Among white females, underweight workers earn the highest average wage of \$6.34. For black females and Hispanic females, obese workers earn the highest average wages of \$5.71 and \$6.44 respectively. On the other hand, among white males and among black males, workers of overweight category earn the highest average wages of \$7.00 and \$8.87 respectively.

The descriptive statistics gives a general impression that workers of recommended weight category earn less than those of non-recommended weight categories, which is counter intuitive. However, no firm conclusion can be drawn from descriptive statistics. Econometric investigation needs to be pursued in order to disentangle the causal effects of weight on wages.

4 Empirical Strategies

4.1 OLS

This study estimates two OLS regressions for each ethno-gender group as baseline models. Wage is modeled as a function of weight and other covariates in both regressions. Continuous BMI is used in one regression and weight categories (obese, overweight, and underweight) are used in other regression as measures of weight. In order to pick the nonlinear effects of obesity, BMI squared is included in the former regression. The latter regression captures the nonlinearity by virtue of the binary nature of the categorical weight variables. Thus the two regressions take the following forms:

$$\ln w_{it} = \alpha + \beta_1 BMI_{it} + \beta_2 BMI_{it}^2 + \boldsymbol{\gamma X_{it}} + \varepsilon_{it} \tag{1}$$

$$\ln w_{it} = \alpha + \beta_1 obese_{it} + \beta_2 overweight_{it} + \beta_3 underweight_{it} + \boldsymbol{\gamma X_{it}} + \varepsilon_{it} \tag{2}$$

where ln w = natural logarithm of wage, *BMI* = body mass index, *obese* = dummy for whether a respondent's BMI is equal to or greater than 30, *overweight* = dummy for whether a respondent's BMI is equal to or greater than 25 and less than 30, *underweight* = dummy for whether a respondent's BMI is less than 18.5, $\boldsymbol{X}$ = vector of other covariates, and ε = error term.[4] Healthy weight is treated as the reference category in equation (2).

4.2 FE

One problem with simple OLS regression is that it gives biased results if key independent variables are endogenous. One of the reasons why measures of weight in the above regressions may be endogenous is unobserved heterogeneity. There might be some unobserved factors in the error term (ε_{it}) that are heterogeneous across respondents and affect weight measures and wage simultaneously. In notation, the problem of unobserved heterogeneity can be defined as the following: $\varepsilon_{it} = u_i + v_{it}$ and $cov(u_i, weight) \neq 0$. As an example, a less driven and careless person can hardly resist eating fatty foods and, hence, is more prone to obesity. Such a person is also highly likely to show poor performance in discharging duties in workplace and hence tends to earn less. Although quite a few socio-economic and attitudinal variables are controlled for, I suspect unobserved heterogeneity still may exist. My conjecture is substantiated by the fact that heterogeneity is apparent in the observables. For example, healthy-weight respondents are more organized, more trustful, and healthier. Their ASVAB scores and parents'

[4] The impact of BMI can be calculated as $\frac{\partial \ln w}{\partial BMI} = \hat{\beta}_1 + 2\hat{\beta}_2 BMI$. The marginal effects of binary weight variable obese can be calculated as $marginal\ effect = \exp(\hat{\beta}_1) - 1$. The marginal effects of overweight and underweight can be calculated in the same way.

highest grade completed appear to be higher than their non-healthy-weight peers. In order to eliminate bias from unobserved heterogeneity, FE models are estimated. For analytical simplicity, it is assumed here that all unobserved heterogeneities are time invariant. FE method can remove such time-invariant heterogeneities.

4.3 FE with Lagged Weight Variables

One other reason why endogeneity may arise is reverse causality. Wage may reasonably contribute to obesity. A person with a lower wage is less able to afford foods with low fat content. As a result, he or she may tend to eat less expensive foods which are generally high in fat. This is how causality may go from wage to obesity. One weakness of the FE method is that it cannot take care of reverse causality. In order to circumvent this problem, FE models are further estimated after replacing contemporaneous weight measures by one-year lags of weight measures.

Reporting error also may cause bias. But since the self-reported weight and height are already corrected for reporting error, the possibility of such bias is reduced.

Because the NLSY97 over-sampled black and Hispanic youths, sampling weights are used wherever possible. Due to the panel nature of the data, each respondent has several observations. To take care of the fact that the error terms between observations of the same respondent are correlated, which in turn reduce the size of standard errors, the cluster command is used in all estimations.

5 Empirical Results

5.1 OLS Results

OLS results for females presented in columns 1, 4, and 7 of Table 4 suggest that there are no significant effects of BMI or the binary weight variables on wages for any group of females.

OLS results for males are reported in columns 1, 4, and 7 of Table 5. These results indicate that BMI has statistically significant nonlinear effects on wages for black males. Positive coefficients on BMI and negative coefficients on BMI squared imply an inverted U-shape relationship of log wages with BMI. Particularly, the magnitudes of the coefficients imply that log wages increase with BMI, reach a peak in the obese region at BMI of 35.7, and then fall for black males. No effect of BMI is apparent for white or Hispanic males.

When BMI and BMI squared are replaced by binary measures of weight, the wages of Hispanic males are again found to be unaffected by weight. Obese black males and overweight black males appear to earn respectively 14.1% and 11.9% more than their healthy-weight counterparts, but there is no significant wage difference between those who are underweight and those of healthy weight. Among white males, underweight workers are found to earn 8.8% less than healthy-weight workers, but no discernible wage differential is apparent for obese or overweight workers compared with their healthy-weight peers.

5.2 FE Results

Columns 2, 5, and 8 of Table 4 display the FE results for females. These results show that switching from OLS to FE does not make any qualitative change in the effects. As in OLS, the coefficients on BMI and three binary weight variables remain statistically insignificant regardless of ethnicity. Some changes in coefficients, however, occur in terms of sign and magnitude, but those changes turn out to be irrelevant due to statistical insignificance.

FE results for males are reported in columns 2, 5, and 8 of Table 5. In the regressions where BMI is used as the measure of weight, the results remain the same in terms of statistical significance for white males and Hispanic males. In other words, coefficients on BMI and BMI squared are still insignificant for these groups. For black males, these coefficients, which were significant in OLS, become insignificant. It gives an indication that significance of these coefficients in OLS is driven by unobserved heterogeneity.

When binary measures of weight are used, no change in statistical significance of the coefficients occurs for Hispanic males. That means, still no significant wage differential is detected between different weight categories for this group. For white males, those who are overweight and those who are obese still appear to earn no different wage then their healthy-weight counterparts. Underweight workers, who were found to be penalized in OLS, also are found to earn the same wage as healthy-weight workers. Among black males, overweight workers seem to earn more than their healthy-weight counterparts, as in the case of OLS, but by an increased magnitude. They are now estimated to earn 17.0% more than the healthy-weight workers compared with 11.9% suggested by OLS. The coefficient on obese, however, loses statistical significance and the coefficient on underweight remains insignificant for this group.

5.3 Results from FE with Lagged Weight Variables

For females, results from FE with lagged weight variables are presented in columns 3, 6, and 9 of Table 4. These results indicate that still no coefficient is significant for all groups of females.

Results for male groups reported in columns 3, 6, and 9 of Table 5 suggest that replacing contemporaneous weight measures by lagged weight measures dramatically changes the coefficients in terms of statistical significance for white males irrespective of the measures of weight used in the regressions. For black males, the results undergo a very little change; only the coefficient of overweight dummy turns insignificant. No qualitative change appears for Hispanic males. In particular, coefficients on BMI and BMI squared for black males and Hispanic males remain insignificant as before. For white males, these coefficients become significant, while they were insignificant in the previous two specifications (OLS and FE). The magnitudes of the coefficients imply that as BMI goes up, log wage of a white male rises, reaches a peak in the obese region at a BMI of 37, and then falls. Figure 1 illustrates this relationship. Results from the regressions in which binary measures of weight are used provide evidence of significant wage differentials relative to healthy-weight workers for only white male workers of overweight category. They are estimated to earn, on average, 5.4% more than their healthy-weight peers.

6 Discussion

An overall look at the results suggests that regardless of the model specifications, weight, be it measured by continuous variable or measured by binary variables, is estimated to have no impact on wages for females of all ethnicities as well as for Hispanic males. For white males and black males, results are seen to vary with the specification, potentially implying the presence of unobserved heterogeneity and reverse causality bias. When continuous measure of weight is used, the FE with lagged weight variables gives significant coefficients on BMI and BMI squared for white males and insignificant coefficients on the same for black males. For white males, these coefficients were insignificant in both OLS and FE models. For black males, these coefficients were significant in OLS models but insignificant in FE models.

When the continuous measure of weight is replaced by the binary measure of weight, the estimates from FE models with lagged weight variables provide evidence of a significant wage premium for those who are overweight among white males. Those who are obese or underweight seem to experience no impact of weight and so is the case for all weight categories in FE and for obese and overweight categories in OLS. For black males, no impact is apparent in the estimates from FE models with lagged weight variables, while OLS estimates indicate a wage premium for obese and overweight categories and no impact for underweight category. FE estimates for this group, on the other hand, suggest a wage premium for the overweight category and no impact for obese and underweight categories.

In sum, after removing unobserved heterogeneity and reverse causality bias, weight does not seem to affect wages for all ethno-gender groups except white males. From the models in which continuous measure of weight is used, it can be predicted that the relationship between lagged BMI and wages is of an inverse U-shape having a peak in the obese region at a BMI of 37. This finding is roughly consistent with the results found from the models in which binary measures of weight instead of continuous measure are used. These results show that those who were overweight in the previous period earn, on average, 5.4% more than their healthy-weight counterparts; substantiating the finding that lagged BMI increases wages up to a certain point.

As noted by McLean and Moon (1980), the positive effect of weight on wages can be explained by the existence of a 'portly banker' effect. Being a non-verbal signal of power, strength and capability, a large body size commands respect and care from co-workers and employers. Thus employers may be willing to pay higher wages to workers of higher weight.

7 Summary and Conclusion

An attempt is taken in this paper to identify the causality between weight and wages. BMI is used as continuous measure of weight, while BMI splines are used as binary measures of weight. A number of explanatory variables are used in order to control for the difference between respondents in human capital, demographic characteristics, socio-economic background, attitudinal status, employment characteristics, ability, health condition, and so on. First of all, an OLS model is estimated. And then a FE specification is used in order to remove time-invariant unobserved heterogeneity in the error term.

Since reverse causality is likely to exist and FE models cannot eliminate the bias resulting from reverse causality, I subsequently replace contemporaneous weight variables by one-year lags of weight variables before estimating FE specification, so the final model of this study is a FE model in which lagged weight variables are used instead of contemporaneous ones.

Separate regressions for each of six ethno-gender groups are estimated in each specification. In all specifications, irrespective of weight measures used, results are the same in terms of statistical significance for all females and Hispanic males: all coefficients are insignificant. For white males and black males, the results vary with the specifications, which implies the potential existence of unobserved heterogeneity and reverse causality. In the final specification, however, significant results are found only for white males. Coefficients on BMI and BMI squared suggest that log wages of white male workers initially increase, reach a peak in the obese region at a BMI of 37, and then fall, as lagged BMI goes up. Results from the regression in which binary measures of weight are used indicate that obese or underweight workers among white males earn no less than their healthy-weight counterparts, but those who are overweight earn 5.4% more. The wage premium for weight can be partly explained by the 'portly banker' effect suggested by Mclean and Moon (1980).

Findings of this study, however, should be viewed with caution due to the following two limitations. First, this study assumes that there is no time varying unobserved heterogeneity, which actually might not be the case. The problem of time-varying unobserved heterogeneity can be appropriately addressed by using IV method, but this study is unable to apply this method due to a lack of suitable instruments. Subject to the availability of data on state level variables, which are not publicly available in the NLSY97, one can try to use some of those variables as instruments to tackle this problem. Second, the cohort involved in this study is younger compared with the cohorts involved in other studies. Age ranges from 18 to 30. As mentioned earlier, the younger the workers, the higher the variability of their wages because of their enrollment status (Averett and Korenman, 1996). Thus the findings cannot be generalized to the workers of older age groups.

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TABLES AND FIGURES

Table 1: Summary statistics (sample means) for females

	All	White	Black	Hispanic	Obese	Overweight	Healthy weight	Underweight
Dependent variable								
Wage (1982 Dollar)	5.449	5.394	5.372	5.756	5.505	5.342	5.468	5.608
Log of wage	1.483	1.484	1.433	1.545	1.476	1.498	1.479	1.463
Key independent variable								
BMI	26.604	25.673	29.343	26.409	36.749	27.107	22.119	17.476
Obese	0.230	0.175	0.377	0.239	-	-	-	-
Overweight	0.248	0.251	0.234	0.255	-	-	-	-
Healthy weight	0.494	0.547	0.357	0.476	-	-	-	-
Underweight	0.027	0.025	0.030	0.029	-	-	-	-
Human capital variables								
Highest grade completed	13.384	13.590	13.134	12.950	13.088	13.437	13.500	13.318
Enrollment status	0.412	0. 432	0. 394	0. 364	0.298	0.377	0.479	0.493
Experience	226.365	242.426	195.190	208.168	238.808	239.809	216.334	180.519
Tenure	77.370	77.750	72.795	82.084	83.902	77.818	74.272	74.183
Demographic variables								
White	0. 614	-	-	-	0.467	0.622	0.681	0.572
Black	0. 220	-	-	-	0.361	0.208	0.159	0.248
Hispanic	0. 164	-	-	-	0.170	0.169	0.158	0.179
Age	21.883	21.853	21.934	21.928	22.470	22.150	21.511	21.235
Weight in kilograms	71.590	70.119	78.596	67.693	98.970	72.916	59.474	47.440
Height in meters	1.639	1.651	1.634	1.599	1.639	1.638	1.638	1.645
Married	0. 145	0. 160	0. 083	0. 174	0.171	0.174	0.122	0.074
Household size	3.376	3.188	3.574	3.817	3.467	3.355	3.350	3.279

Table 1 (Continued)

	All	White	Black	Hispanic	Obese	Overweight	Healthy weight	Underweight
Number of household member	0.702	0.539	1.019	0.888	0.823	0.733	0.635	.615
Number of kids	0.028	0.030	0.031	.015	0.035	0.044	0.015	0.052
Urban residence	0.797	0.738	0.869	0.920	0.782	0.807	0.796	0.842
Birth country is US	0.845	0.911	0.909	0.510	0.884	0.858	0.827	0.707
Northeast region	0. 163	0. 179	0. 122	0. 156	0.150	0.171	0.166	0.135
North-central region	0. 240	0. 310	0. 149	0. 104	0.203	0.241	0.260	.205
West region	0. 226	0. 215	0. 059	0. 488	0.188	0.213	0.253	0.170
South region	0. 369	0. 294	0. 667	0. 250	0.457	0.373	0.319	0.489
Employment characteristics								
White collar	0.586	0.568	0.609	0.622	0.592	0.575	0.586	0.628
Part time	0.228	0.255	0.187	0.181	0.177	0.217	0.251	0.318
Industry								
Agriculture	0.004	0.006	0.000	0.002	0.004	0.006	0.003	0.000
Mining	0.000	.001	0.000	0.000	0.001	0.000	0.000	0.000
Utilities	0.000	0.000	0.000	0.002	0.001	0.001	0.000	0.000
Construction	0.007	0.009	0.003	0.008	0.005	0.008	0.007	0.013
Manufacturing	0.030	0.032	0.028	0.025	0.042	0.032	0.024	0.017
Transportation	0.015	0.013	0.022	0.011	0.022	0.016	0.012	0.000
Wholesale	0.011	0.012	0.007	0.014	0.007	0.011	0.012	0.017
Retail	0.215	0.202	0.233	0.242	0.204	0.215	0.220	0.227
Finance	0.060	0.053	0.049	0.101	0.047	0.069	0.063	0.043
Information	0.023	0.024	0.030	0.011	0.028	0.018	0.023	0.021
Education	0.246	0.247	0.242	0.250	0.270	0.237	0.239	0.270
Entertainment	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Professional	0.091	0.094	0.088	0.080	0.087	0.096	0.087	0.135
Food	0.209	0.221	0.203	0.175	0.183	0.207	0.224	0.179

Table 1 (Continued)

	All	White	Black	Hispanic	Obese	Overweight	Healthy weight	Underweight
Public administration	0.018	0.014	0.032	0.015	0.017	0.018	0.018	0.039
Public administration	0.018	0.014	0.032	0.015	0.017	0.018	0.018	0.039
Others	0.062	0.066	0.057	0.056	0.074	0.061	0.058	0.034
Attitude variables								
Mental health index	14.870	14.953	14.800	14.653	14.985	14.907	14.836	14.165
Disorganized	2.323	2.336	2.307	2.295	2.446	2.388	2.235	2.266
Conscientious	3.545	3.670	3.319	3.381	3.442	3.526	3.613	3.344
Undependable	1.639	1.584	1.652	1.828	1.631	1.656	1.637	1.593
Agreeable	3.849	3.893	3.837	3.705	3.878	3.837	3.882	3.934
Thorough	3.838	3.904	3.793	3.652	3.782	3.741	3.860	3.995
Difficult	2.108	2.085	2.080	2.229	2.116	2.126	2.100	2.021
Trustful	4.477	4.497	4.433	4.461	4.465	4.461	4.491	4.449
Other variables								
ASVAB	53.920	63.088	37.688	41.434	47.200	53.906	57.218	51.121
Lived with both bioparents in 1997	0.620	0.682	0.407	0.674	0.522	0.598	0.678	0.606
Father’s highest grade completed	12.967	13.649	12.563	10.963	12.294	12.910	13.318	12.829
Mother’s highest grade completed	13.082	13.763	12.762	10.967	12.600	13.123	13.284	13.109
Household net worth at age 20	8696.238	9702.792	4286.709	10847.100	8476.743	7938.822	9198.716	8339.345
Health condition	2.160	2.094	2.278	2.247	2.522	2.172	1.991	2.048
Smoking	0.367	0.435	0.216	0.316	0.383	0.394	0.352	0.257
Number of cigarette per day in last month	2.444	3.144	1.150	1.562	3.063	2.868	1.989	1.593
Drinking	0.774	0.840	0.613	0.743	0.747	0.796	0.776	0.746
Number of drinks per day in last month	2.289	2.606	1.391	2.309	2.184	2.267	2.374	1.838
Marijuana	0.218	0.250	0.162	0.170	0.195	0.213	0.228	0.266
Cocaine	0.057	0.073	0.015	0.057	.035	0.069	0.062	0.069

Table 2: Summary statistics (sample means) for males

	All	White	Black	Hispanic	Obese	Overweight	Healthy weight	Underweight
Dependent variable								
Wage (1982 Dollar)	6.647	6.680	7.005	6.148	6.716	7.155	6.372	5.247
Log of wage	1.605	1.625	1.552	1.580	1.600	1.672	1.571	1.476
Key independent variables								
BMI	26.076	25.586	27.149	26.894	35.055	27.129	22.208	17.367
Obese	0.196	0.168	0.255	0.243	-	-	-	-
Overweight	0.292	0.297	0.269	0.297	-	-	-	-
Healthy weight	0.490	0.511	0.454	0.444	-	-	-	-
Underweight	0.019	0.021	0.020	0.013	-	-	-	-
Human capital variables								
Highest grade completed	12.802	13.039	12.241	12.449	12.625	13.026	12.756	12.360
Enrollment status	0.340	0.362	0.280	0.317		0.307	0.392	0.434
Experience	230.956	245.768	191.450	213.620	262.976	254.090	206.141	186.371
Tenure	80.862	85.907	66.865	75.516	93.582	88.496	70.853	89.737
Demographic variables								
White	0.659	-	-	-	0.566	0.670	0.687	0.708
Black	0.173	-	-	-	0.226	0.159	0.160	0.177
Hispanic	0.167	-	-	-	0.207	0.170	0.151	0.114
Age	21.900	21.863	22.047	21.890	22.539	22.392	21.387	21.000
Weight in kilograms	83.092	82.259	86.634	82.698	112.198	85.998	70.732	57.896
Height in meters	1.783	1.791	1.783	1.752	1.787	1.779	1.783	1.828
Married	0.100	0.100	0.074	0.129	0.169	0.121	0.063	0.051
Household size	3.420	3.282	3.358	4.024	3.436	3.358	3.439	3.691
Number of household member under age 18	0.548	0.447	0.643	0.848	.630	0.522	0.528	0.622
Number of kids	0.168	0.072	0.491	0.209	0.222	0.187	0.138	0.068

Table 2 (continued)

	All	White	Black	Hispanic	Obese	Overweight	Healthy weight	Underweight
Urban residence	0.772	0.733	0.779	0.921	0.761	0.777	0.777	0.685
Birth country is US	0.853	0.916	0.900	0.556	0.875	0.859	0.840	0.862
Northeast region	0.159	0.182	0.112	0.117	0.148	0.167	0.158	0.177
North-central region	0.268	0.331	0.202	0.090	0.241	0.282	0.274	0.188
West region	0.235	0.207	0.068	0.515	0.208	0.235	0.243	0.280
South region	0.336	0.277	0.615	0.276	0.401	0.314	0.322	0.354
Employment characteristics								
White-collar	0.355	0.370	0.283	0.367	0.308	0.363	0.368	0.360
Part time	0.150	0.163	0.131	0.121	0.125	0.121	0.175	0.228
Industry								
Agriculture	0.013	0.016	0.003	0.010	0.017	0.019	.008	0.005
Mining	0.006	0.006	0.009	0.004	0.011	0.004	.005	0.000
Utilities	0.005	0.006	0.005	0.004	0.002	0.006	.007	0.000
Construction	0.118	0.132	0.071	0.110	0.099	0.132	.117	0.120
Manufacturing	0.099	0.093	0.117	0.102	0.106	0.103	.095	0.068
Transportation	0.037	0.029	0.062	0.042	0.045	0.041	.030	0.057
Wholesale	0.027	0.027	0.026	0.028	0.036	0.026	.023	0.051
Retail	0.181	0.187	0.158	0.179	0.200	0.163	.181	0.257
Finance	0.039	0.042	0.029	0.036	0.030	0.041	.042	0.005
Information	0.024	0.024	0.029	0.023	0.020	0.022	.028	0.017
Education	0.086	0.085	0.076	0.102	0.075	0.085	.089	0.131
Entertainment	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Professional	0.102	0.096	0.117	0.112	0.111	0.101	.102	0.057
Food	0.189	0.191	0.198	0.174	0.164	0.176	.208	0.177
Public administration	0.017	0.015	0.026	0.018	0.033	0.019	.010	0.000
Others	0.048	0.044	0.064	0.048	0.040	0.053	.048	0.051

Table 2 (continued)

	All	White	Black	Hispanic	Obese	Overweight	Healthy weight	Underweight
Attitude variables								
Mental health index	15.867	15.846	16.032	15.780	15.816	15.848	15.908	15.634
Disorganised	2.483	2.530	2.407	2.378	2.563	2.500	2.443	2.445
Conscientious	3.361	3.423	3.163	3.320	3.300	3.420	3.341	3.571
Undependable	1.747	1.712	1.788	1.838	1.773	1.764	1.722	1.834
Agreeable	3.772	3.749	3.833	3.800	3.735	3.710	3.818	3.920
Thorough	3.749	3.727	3.770	3.813	3.729	3.726	3.769	3.782
Difficult	2.154	2.191	2.105	2.061	2.220	2.209	2.093	2.228
Trustful	4.352	4.362	4.320	4.347	4.315	4.321	4.393	4.171
Other variables								
ASVAB	50.005	58.193	30.752	37.738	45.695	49.888	52.034	44.243
Lived with both bioparents in 1997	0.656	0.706	0.459	0.659	0.620	0.659	0.664	0.742
Father's highest grade completed	12.921	13.654	12.152	10.832	12.376	12.808	13.210	12.828
Mother's highest grade completed	13.073	13.688	12.722	11.017	12.549	12.916	13.392	12.702
Household net worth at age 20	11907.1000	12628.720	6763.066	14402.290	11517.410	12504.820	11840.010	8612.537
Health condition	2.004	1.980	1.998	2.104	2.387	2.019	1.846	1.891
Smoking	0.455	0.478	0.411	0.407	0.412	0.442	.486	0.297
Number of cigarette per day in last month	3.843	4.564	3.055	1.823	3.575	3.602	4.128	3.005
Drinking	0.766	0.810	0.638	0.725	0.765	0.776	0.771	0.508
Number of drinks per day in last month	3.893	4.125	2.425	4.502	3.988	4.086	3.815	2.045
Marijuana	0.278	0.300	0.253	0.219	0.210	0.244	0.332	0.154
Cocaine	0.066	0.081	0.028	0.046	0.049	0.066	0.075	0.017

Table 3: Sample means of wages (1982 Dollar) for different ethno-gender groups

	Females			Males		
	White	Black	Hispanic	White	Black	Hispanic
Obese	5.004	5.713	6.439	6.978	7.341	5.321
Overweight	5.5	5.052	5.110	7.002	8.866	6.150
Healthy weight	5.426	5.297	5.818	6.440	5.811	6.660
Underweight	6.335	4.503	4.820	5.544	4.780	4.128

Table 4: Results of log wage regressions[a]: females

	White Females			Black Females			Hispanic Females		
	OLS	FE	FE with lag weight	OLS	FE	FE with lag weight	OLS	FE	FE with lag weight
	1	2	3	4	5	6	7	8	9
BMI	-0.005 (0.509)	-0.008 (0.510)	-0.004 (0.265)	0.001 (0.872)	-0.011 (0.614)	-0.001 (0.948)	0.027 (0.190)	0.007 (0.840)	0.040 (0.710)
BMISQ	0.000 (0.680)	0.000 (0.422)	0.000 (0.107)	-0.000 (0.622)	0.000 (0.750)	-0.000 (0.973)	-0.000 (0.213)	-0.000 (0.809)	-0.000 (0.841)
Obese	-0.027 (0.322)	0.059 (0.177)	0.022 (0.591)	-0.038 (0.345)	-0.016 (0.799)	-0.013 (0.828)	0.057 (0.362)	0.063 (0.477)	0.013 (0.852)
Overweight	0.013 (0.556)	0.041 (0.169)	0.018 (0.488)	-0.010 (0.797)	0.025 (0.580)	0.029 (0.499)	-0.053 (0.262)	-0.009 (0.856)	0.043 (0.424)
Underweight	-0.027 (0.680)	0.171 (0.198)	0.067 (0.450)	0.055 (0.417)	0.068 (0.540)	0.050 (0.529)	-0.076 (0.203)	-0.075 (0.398)	0.063 (0.437)

[a] For BMI and BMI squared, coefficients and p-values are reported. For binary weight variables, the percentage changes in wage due to change in binary variable from 0 to 1 and p-values are reported.

Table 5: Results of log wage regressions[a]: males

	White Males			Black Males			Hispanic Males		
	OLS	FE	FE with lag weight	OLS	FE	FE with lag weight	OLS	FE	FE with lag weight
	1	2	3	4	5	6	7	8	9
BMI	0.008	0.019	0.024***	0.050**	0.036	0.010	0.029	0.050	0.004
	(0.463)	(0.261)	(0.010)	(0.013)	(0.129)	(0.311)	(0.254)	(0.164)	(0.751)
BMISQ	-0.000	-0.000	-0.0003**	-0.0007**	-0.001	-0.000	-0.001	-0.001	0.000
	(0.483)	(0.357)	(0.022)	(0.024)	(0.109)	(0.437)	(0.179)	(0.167)	(0.825)
Obese	-0.026	-0.005	0.006	0.141**	0.130	0.024	-0.056	-0.007	-0.034
	(0.486)	(0.912)	(0.901)	(0.021)	(0.253)	(0.842)	(0.240)	(0.917)	(0.629)
Overweight	0.016	0.026	0.054*	0.119**	0.170**	0.041	0.010	-0.004	-0.004
	(0.483)	(0.317)	(0.059)	(0.029)	(0.013)	(0.527)	(0.822)	(0.933)	(0.914)
Underweight	-0.088*	-0.040	-0.024	-0.069	0.129	0.158	-0.231	-0.346	-0.112
	(0.067)	(0.554)	(0.714)	(0.551)	(0.185)	(0.168)	(0.101)	(0.131)	(0.353)

[a] For BMI and BMI squared, coefficients and p-values are reported. For binary weight variables, the percentage changes in wage due to change in binary variable from 0 to 1 and p-values are reported.

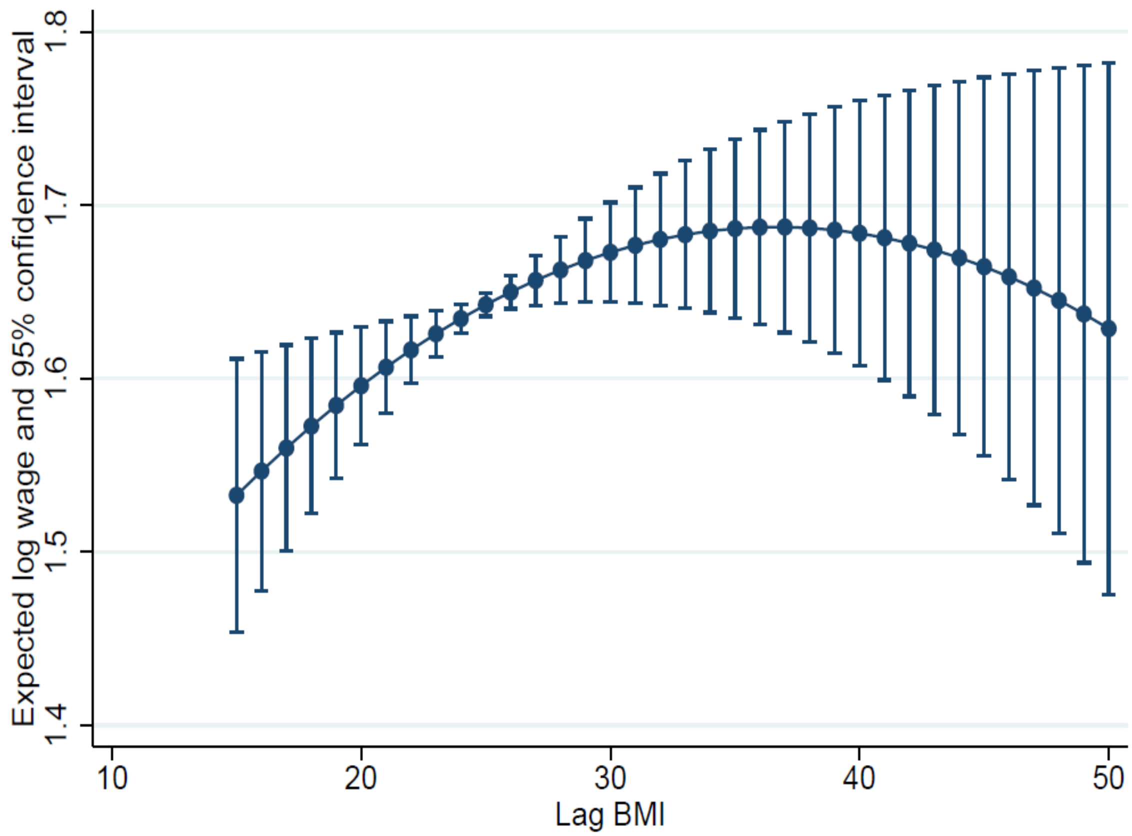

Figure 1: Relation between lag BMI and log wage: white males (FE estimates with lag weight)

OVERALL CONCLUSION

In the face of growing labor market difficulties and increasing need for understanding labor market dynamics in the US, it is important to investigate factors that determine labor market outcomes in this country. Throughout the three chapters of this dissertation, I focus on a couple of those factors to see if they have causal effects on labor market outcomes in the US.

Using data drawn from the US Census 2000 PUMS 5% File, I examine the effects of homeownership on employment and wages in the first chapter entitled “The Effects of Homeownership on Labor Market Outcomes: Evidence from the United States”. For the sake of precise estimation, I distinguish between mortgagers (homeowners with mortgage liabilities) and outright owners (homeowners with no mortgage liabilities). I use logit and OLS as baseline specifications in the employment model and the wage model, respectively. The MSL approach is applied in both models to get rid of potential endogeneity. To get robust results, I use two instrumental variables. Findings provide evidence of the beneficial effects of homeownership. Particularly, outright owners are found to have more likelihood of being employed, and earn higher wages than renters. Mortgagers are also found to have higher employment probability compared to renters. But they seem to be no different than renters in terms of wages.

In the second chapter entitled “Does Parenting Style Matter for Labor Market Outcomes? Evidence from the United States”, I attempt to see if parenting style has any causal impact on children’s adult labor market outcomes using the NLSY97. Four labor market outcomes, namely, wages, number of weeks worked, number of weeks unemployed, and probability of having white collar job, are examined employing logit and OLS as empirical strategies. Evidence from this study suggests that parenting style does matter for labor market outcomes. AVPS is found to be the most beneficial among four categories of parenting style. PPS appears to be better than UPS only in terms of weeks worked. In terms of other labor market outcomes, it is no different than UPS. ANPS, on the other hand, is found as good as UPS across the series of estimations performed.

I close the dissertation with the chapter entitled “Does Obesity Matter for Wages? Evidence from the United States” in which data come from the NLSY97. Obesity is measured by BMI (a continuous variable) and BMI splines (several categorical variables). I use OLS and FE estimation methods as empirical strategies. FE estimation takes care of time invariant unobserved heterogeneity. In addition to regular FE specification, I use an FE specification with contemporaneous weight variables being replaced by one-year lags of weight variables in order to mitigate reverse causality. Results from this chapter shows that white males receive a wage premium for higher BMI. No impact of obesity on wages is evident for all other ethno-gender groups.

An overall assessment of the findings of this dissertation reveals that in the US, household behavior and health factor play nontrivial roles in the determination of labor market outcomes. Particularly, homeownership status, and parenting style one experience in his/her childhood have profound impact on labor market success. On the other hand, although obesity does not have significant effects on the wages of white females, blacks or Hispanics, it does matter for white males.