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Essays on Health and Labor Market Practices in the U.S.

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ESSAYS ON HEALTH AND LABOR MARKET PRACTICES IN THE U.S.

by

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ABSTRACT

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This dissertation investigates the link between different aspects of labor market and individuals' health. The first chapter analyzes the relationship between the use of four different substances and nonstandard work schedules. Using the NLSY97 and applying standard panel techniques as well as survival analyses, I find that contrary to most previous evidence, nonstandard work schedule is not necessarily associated with an increase in substance use, and in the case of drinking and binge drinking such correlation is actually negative. Evidence also suggests that drug prone individuals tend to work more at nonstandard schedules. Results are robust to the specification at the intensive margin and accounting for long-term exposure to work at nonstandard schedules. The second chapter investigates the effect of alcohol use on job search behavior of young individuals. Using the age of respondents from the NLSY97 both in the year and month formats and applying regression discontinuity design by utilizing the surge in alcohol consumption at age 21, I find that young adults tend to increase their drinking and binge drinking once they are allowed to legally access alcohol. However, I find that the surge in alcohol use at age 21 does not seem to immediately or directly affect the job search behavior of young individuals while they are employed or unemployed. I also find that it does not seem to affect their lack of desire for work. The third

chapter investigates the effects of workers' age, gender, and race relative to those of their supervisors on several measures of the employees' mental wellbeing. Evidence suggests that men show positive mental health signs when they have supervisors of same gender and race. They also seem to like supervisors who are almost the same age. On the contrary, women's mental health seems to be negatively affected when they have female supervisors. When the gender match effect is combined with race, it is magnified. Women also report negative mental health signs when all these demographic characteristic matches are happening at the same time. Additional tests suggest that reverse causality does not seem to be a major issue here.

To

my amazing parents who made me proud my whole life,

and my beautiful sister, Melody, who will always shine in my heart

and my baby brother, Mohammad, whose company cannot be beaten…

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Chapter 1- The Relationship between Nonstandard Work Schedules and Substance Use

New Evidence from the NLSY97

Mona Khadem Sameni[1]

June 2016

Abstract

This paper analyzes the relationship between the use of four different substances and nonstandard work schedules. Using the NLSY97 and applying standard panel techniques as well as survival analyses, I find that contrary to most previous evidence, nonstandard work schedule is not necessarily associated with an increase in substance use, and in the case of drinking and binge drinking such correlation is actually negative. Evidence also suggests that drug prone individuals tend to work more at nonstandard schedules. Results are robust to the specification at the intensive margin and accounting for long-term exposure to work at nonstandard schedules.

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I. Introduction :

About one fifth of the U.S. wage and salary workers are employed at nonstandard schedules such as regular nights, regular evenings, rotating or split shifts (McMenamin, 2007). A number of previous studies have argued that such schedules or "shift work" may interrupt the employees' daily routines and thus could harm their health through psychosocial (Drake et al., 2004; Wirtz and Nachreiner, 2010; Srivastava, 2010) or physiological mechanisms (Finn, 1981; Harrington, 2001; Arendt, 2010; Dorrian and Skinner, 2012; Davis et al., 2012). A few other papers have suggested that shift workers may use alcohol, tobacco, or illicit drugs to combat the effects of circadian rhythm disruptions (Knauth and Hornberger, 2003; Bushnell et al., 2010; Dorrian and Skinner, 2012).

This paper offers new evidence on the correlation between shift work[2] and the consumption of four different substances. Its main contribution is the use of longitudinal data to investigate this correlation. Nearly all previous work in this area has examined cross-sectional data, the exceptions being two studies (Dorrian and Skinner, 2012 and Ulker, 2006) that used only two waves of the Household, Income and Labour Dynamics in Australia (HILDA). This aspect is particularly important, because longitudinal data provides a way to address the possibility that the previous cross sectional evidence on higher substance use among shift workers does not represent a causal effect, but rather the sorting of individuals who are prone to substance use into the jobs with nonstandard schedules.

A better sense of the direction of this cause-and-effect relationship matters because if previous evidence was accurate and shift work actually caused increases in substance use, some public

[2] Although shift work and work at nonstandard schedules are technically different, for conciseness, they are used interchangeably.

health enhancing provisions to discourage shift work would seem appropriate. Alternatively, firms might need to pay higher compensating differentials to the shift workers. However, note that firms might plausibly be willing to pay those compensating differentials if they use shift work to increase their production. If shift work did not actually create health problems (or even if those problems were internalized through a compensating differential), policies mistakenly intended to combat those concerns could have a significant social cost. Currently, although there are some provisions for shift differentials by the Federal and some state and local governments, the Employment Compensation Survey conducted by The Bureau of Labor Statistics in June 2012 shows such differentials are very small. [3]

Using fifteen waves of the NLSY97, I find that much of the positive relationship between substance use and shift work vanishes when I control for permanent differences across workers via fixed effects estimates. In fact – and in contrast to what several previous studies suggested– I find strong evidence that shift work reduces the alcohol used by both men and women. Moreover, some estimates do suggest that shift work causes modest increases in smoking and drug use, but some of these results are fairly weak or fragile – especially for smoking. As a general rule, most coefficients lose some statistical significance when I control for individual fixed effects.

The rest of the paper is structured as follows. Section II explores the related literature. Section III discusses the data and methodology. Section IV presents the results, and Section V concludes.

[3] See http://www.opm.gov/policy-data-oversight/pay-leave/pay-administration/fact-sheets/night-shift-differential-for-federal-wage-system-employees/

II. Background :

Nonstandard work schedules have long been an important part of the working Americans' lives. According to Presser and Ward (2011), almost 90% of the people aged 14-18 in 1979 experienced some type of shift work by age 39. As Hamermesh (1999) discusses, one major motivation for employers to use shift work is the variation in the employers' product demand by time of the day (and day of the week). Other major demand determinants are the needs for nonstop manufacturing and to keep production processes separate.

Shift work appears to be less attractive to workers, however. According to McMenamin (2007), the majority of shift workers (about 55%) pick nonstandard hours for involuntary reasons such as the inability to find better jobs, and only 10% express personal preference for such job choice. If so, this would suggest a reason to fear that workers who are more prone to substance use might also be more likely to do shift work: it is natural to imagine that such workers may have fewer job opportunities, and thus they may be more likely to accept unattractive working conditions. It is thus important to take seriously the possibility of reverse causality, and this is one of the main motives for this paper's use of longitudinal data.

On the other hand, a number of previous studies claim that shift work might have negative consequences for an individual's health. Finn (1981) believes the main reason behind the occurrence of such negative impacts on health is being "out of rhythm" with daily routines that affects minds as well as bodies. Trinkoff and Storr (1998) use some cross sectional evidence to show that the long exposure to shift work increases the prevalence of drinking, smoking, and drug use. Shields (2002) presents some Canadian evidence that shift work might add to personal stress and thus can change eating habits as well as smoking and drinking behaviors.

Nonetheless, Ulker (2006) and Dorrian and Skinner (2012) are the only two longitudinal studies to test the relationship between shift work and the potential impacts on health, and both use the HILDA. Ulker (2006) is able to show that working at nonstandard schedules is generally negatively associated with better health conditions, but in some cases he finds positive correlations with better physical and mental health for women. Dorrian and Skinner (2012) show that according to the 2001 Australian government alcohol guidelines, overall being a shift worker significantly increases the short-term odds of drinking alcohol risky levels, though they also find that average daily alcohol consumption decreases.

While these studies are a methodological advance, they are still limited to consideration of just two waves of an Australian longitudinal dataset. In this paper, I extend their empirical strategy significantly by examining fifteen rounds of an American panel data, and I find some complementary evidence that shift work is not necessarily positively correlated with substance use. In addition, factoring out the permanent differences across the individuals actually makes the positive correlations smaller.

III. Data and Methodology

A) Data, Descriptive Statistics, and Survival Plots

This study uses rounds 1-15 of the U.S. National Longitudinal Survey of Youth (NLSY 97), starting in 1997 and ending in 2011. This individual-level survey provides detailed annual information on the number of days that an individual smoked cigarettes, drank alcohol, had five or more drinks on the same occasion (which will hereafter be called “binge drinking”), or used marijuana within the 30 days prior to the survey. Another key question asks about the number of times that the respondent used cocaine or any other hard drugs within the past year. Each round

also contains data on the respondents' work schedules: Regular day shift, regular evening shift, regular night shift, shift rotates, split shifts, irregular schedules or hours, weekends, and part time. As in previous work, due to the scarcity of workers in some of the nonstandard schedules, any work schedule other than regular day schedule will be considered shift work.

One advantage of this longitudinal dataset for the purpose of the current study is the focus on a young cohort. This is potentially beneficial because at this age people are more likely to use substances and (perhaps more importantly) to establish addictive behaviors that persist throughout their lives. Moreover, young people are also more likely to do shift work. However, one drawback is that this cohort does not represent the whole population, so the estimated effects cannot be examined at other ages.

Round 1 of the survey starts with 8,984 individuals who were interviewed annually for 15 consecutive rounds unless they died or left the sample. Table 1.1 summarizes the combined work schedule and employment status distribution of the person-years by gender. It shows that less than half of the employed civilians in this sample work at irregular schedules. Since my goal is to test the relationship between shift work and substance use, only employed individuals will be kept in the sample analyzed below.

Table 1.1- Shift work and Employment Status Distribution of Person-years

	Employed regular day schedule	Employed shiftwork	Unemployed	Out of the Labor Force/Indeterminate	Military	No information	Total
Males	15,808 22.92	15,860 22.99	1,020 1.48	4,209 6.10	468 0.68	31,620 45.84	68,985 100.00
Females	15,658 23.81	15,334 23.31	707 1.07	4,443 6.75	71 0.75	29,562 44.94	65,775 100.00
Total	31,466 23.35	31,194 23.15	1,727 1.28	8,652 6.42	539 0.40	61,182 45.40	134,760 100.00

The number and percentage of person-years in different employment categories based on gender.

Table 1.2 offers summary statistics on the intensity of substance use by shift workers and regular day workers. The upshot of this table is that on average, the intensity of alcohol use (days in the past month with drinking or binge drinking) is higher for regular day workers compared to shift workers. Furthermore, the intensity of smoking and drug use is higher and more dispersed for shift workers.

Table 1.2- Summary Statistics of the Final Sample

	Drinking	Binge Drinking	Smoking	Using Marijuana	Using Cocaine/Hard Drugs
Number of Shift working person-years	22744	22635	22792	22884	22354
Frequency of Behavior	4.330 (6.178)	1.620 (3.616)	7.357 (12.146)	2.028 (6.504)	2.159 (24.299)
Number of Non-Shift Working Person-years	21073	20900	21124	21234	21133
Frequency of Behavior	4.769 (6.495)	1.672 (3.751)	6.882 (11.874)	1.811 (6.264)	1.378 (19.287)

The frequency of behavior is the average number of days in the past month that the respondents reported using the substances. For cocaine/hard drugs the frequency is the average number of times of use in the past year. The figures in the parentheses report standard deviations.

Table 1.3 presents the percentage of person-years in different schedules across the industries. As expected, the shift working respondents are employed at industries that are more common for student/early career life. To retain some homogeneity in the study sample, the main statistical analyses below will be given after controlling for industry effects.

Table 1.3-Shift Work Percentages of Person-years across the Industries

	Regular day schedule	Regular Second/Third Shift	Irregular Schedules
Agriculture, Forestry and Fisheries	53.04	9.62	37.34
Mining	60.67	5.44	33.89
Utilities	86.60	3.35	10.05
Construction	86.24	2.01	11.75
Manufacturing	63.34	23.91	12.76
Wholesale Trade	73.37	15.15	11.48
Retail Trade	37.15	25.03	37.82
Arts, and Recreation	N/A	N/A	N/A
Transportation and Warehouse	52.36	24.28	23.37
Information and Communication	55.13	17.99	26.89
Finance, Insurance and Real Estate	77.17	9.42	13.41
Professional Services	69.22	14.40	16.38
Educational, Health and Social Services	63.88	16.56	19.56
Entertainment, Accommodation and Food	27.80	34.44	37.75
Other Services	59.69	12.44	27.87
Public Administration	62.29	17.06	21.67
Active Duty Military	61.28	6.29	31.43
Special Codes	54.05	9.19	36.76

Each column reports percentages of each type of shift work for different industries.

Table 1.4 shows the use percentage of various substances by the employed sample. Contrary to what we might have imagined based on the previous studies, substance use rates are not always

higher for shift workers. Moreover, substance use rates are always lower for women, married and black people. In addition, in some cases more educated people use more substances.

Table 1.4- Percentage of Workers Using Various Substances, By Demographics and Shift Work

4-a

Selected Demographics	Drinking			Binge Drinking		
	Shift Work	Regular Day Work	Total	Shift Work	Regular Day Work	Total
Gender						
Male	65.18	71.43	68.22	42.68	46.82	44.69
Female	62.59	63.70	63.12	29.17	26.81	28.05
Race						
Black	50.09	53.69	51.67	21.02	20.73	20.89
Hispanic	62.01	62.71	62.39	36.00	34.88	35.39
Mixed Race	64.22	67.39	65.72	39.11	31.32	35.42
Non-Black	70.03	74.52	72.16	41.72	43.46	42.54
Marital Status						
Married	59.31	63.35	67.02	29.08	31.13	30.17
Unmarried	65.19	69.08	61.46	37.48	38.65	38.03
Highest Degree						
High School	62.84	65.66	64.18	35.61	36.31	35.94
Associate and Bachelor's	68.93	75.07	72.01	37.77	39.76	38.77
Graduate Degree	72.47	76.64	74.90	37.34	36.07	36.60
Professional Degree	75.27	78.46	76.58	33.33	30.77	32.28

4-b

Selected Demographics	Smoking			Using Marijuana		
	Shift Work	Regular Day Work	Total	Shift Work	Regular Day Work	Total
Gender						
Male	36.41	37.67	37.02	18.20	16.97	17.60
Female	33.29	27.18	30.38	14.29	10.10	12.30
Race						
Black	23.78	21.99	23.00	12.95	12.26	12.65
Hispanic	30.73	27.14	28.78	14.00	10.79	12.26
Mixed Race	39.22	33.70	36.60	18.63	14.13	16.49
Non-Black	40.56	38.37	39.52	18.24	15.22	16.81
Marital Status						
Married	30.64	26.62	28.50	10.35	7.72	8.95
Unmarried	35.67	33.88	34.83	17.55	15.21	16.45
Highest Degree						
High School	37.72	35.43	36.63	16.71	14.32	15.57
Associate and Bachelor's	24.23	22.38	23.30	14.74	11.29	13.01
Graduate	17.61	12.90	14.87	12.58	8.39	10.14

Degree						
Professional Degree	9.68	23.08	15.19	10.75	13.85	12.03

4-c

Selected Demographics	Using Cocaine or Hard Drugs		
	Shift Work	**Regular Day Work**	**Total**
Gender			
Male	5.91	4.66	5.30
Female	5.26	2.70	4.03
Race			
Black	1.24	0.98	1.12
Hispanic	6.63	2.82	4.55
Mixed Race	7.88	2.73	5.44
Non-Black	6.99	5.03	6.05
Marital Status			
Married	4.18	1.88	2.94
Unmarried	5.90	4.18	5.09
Highest Degree			
High School	5.78	3.85	4.85
Associate and Bachelor's	5.20	3.26	4.22
Graduate Degree	3.25	1.59	2.28
Professional Degree	1.11	4.62	2.58

A nice feature of the longitudinal data is that the hazard ratios of the onset of using substances by the treatment group (the shift workers) can be compared to those of the control group (the regular day workers). Figures 1.1-1.5 present the Kaplan-Meier non parametric survival plots (Kaplan and Meier, 1958) for different types of substances separately. In all these figures, the dashed line represents the shift workers and as it can be seen, the hazard rate of the onset of drinking and binge drinking appear to be lower for shift workers. In the case of smoking, using marijuana and cocaine/hard drugs, however, the hazard rates seem higher for shift workers or almost any differences seem nonexistent at some points. Of course, it should be emphasized that these plots do not consider the effects of any confounding factors.

Figure 1.1-Survival Plots for Drinking

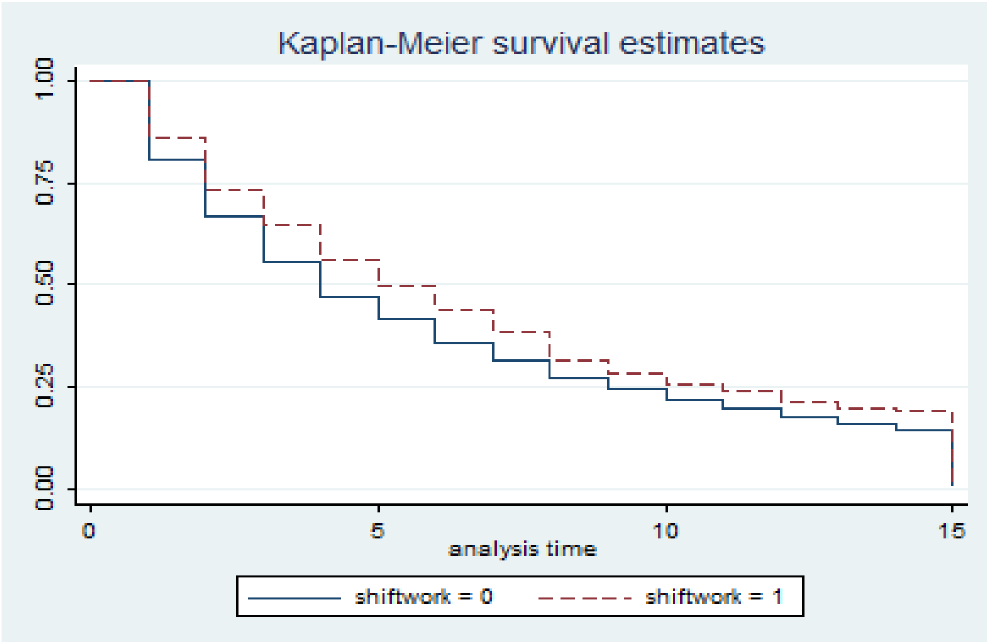


Figure 1.2-Survival Plots for Binge Drinking

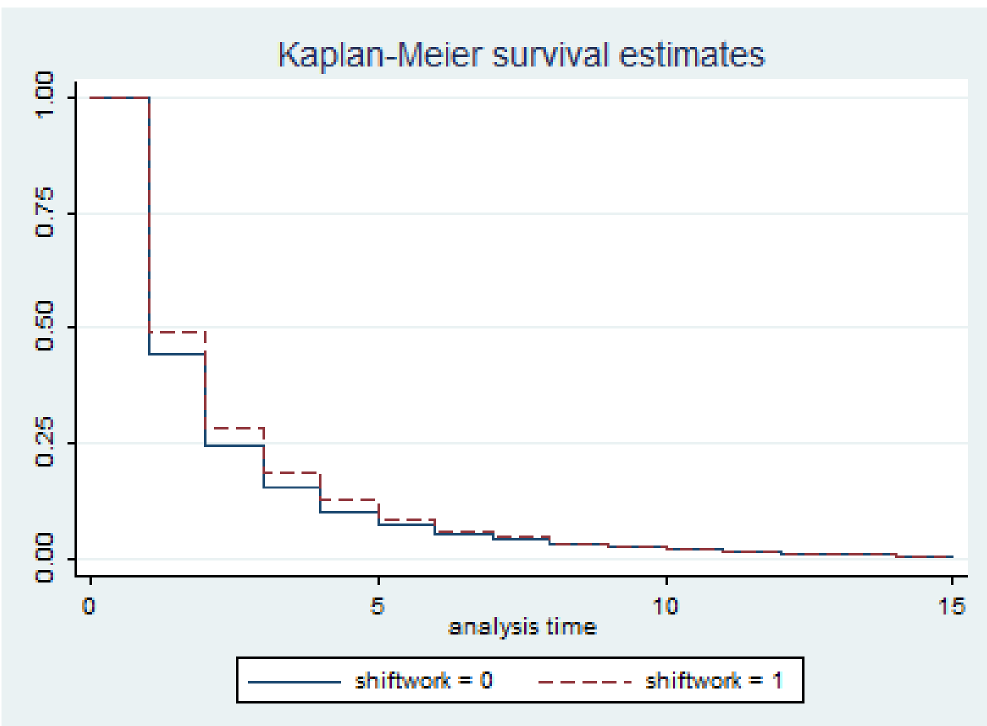


Figure 1.3-Survival Plots for Smoking

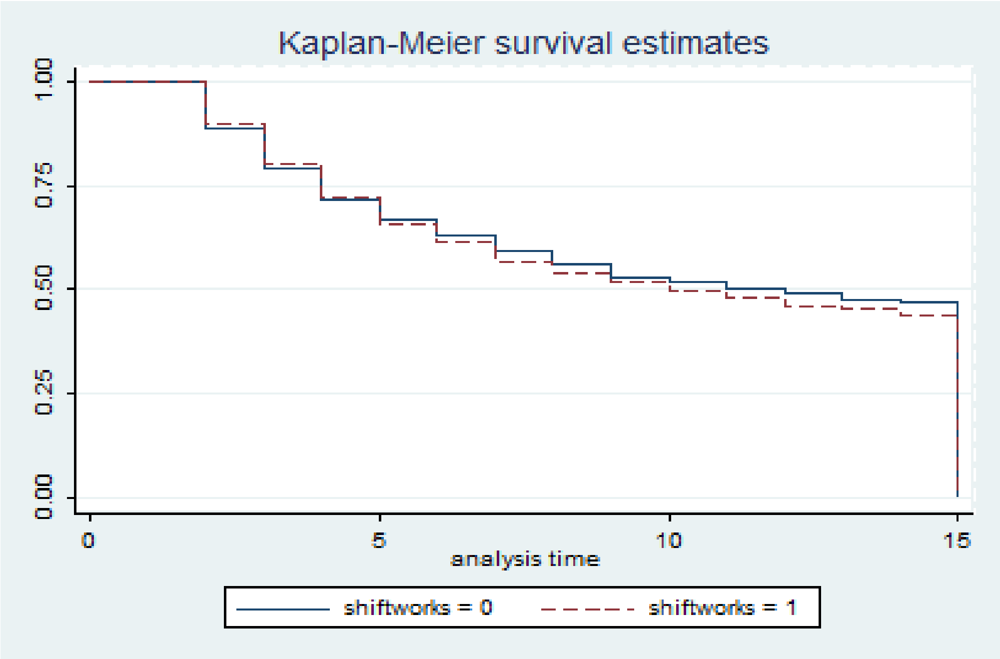


Figure 1.4-Survival Plots for Using Marijuana

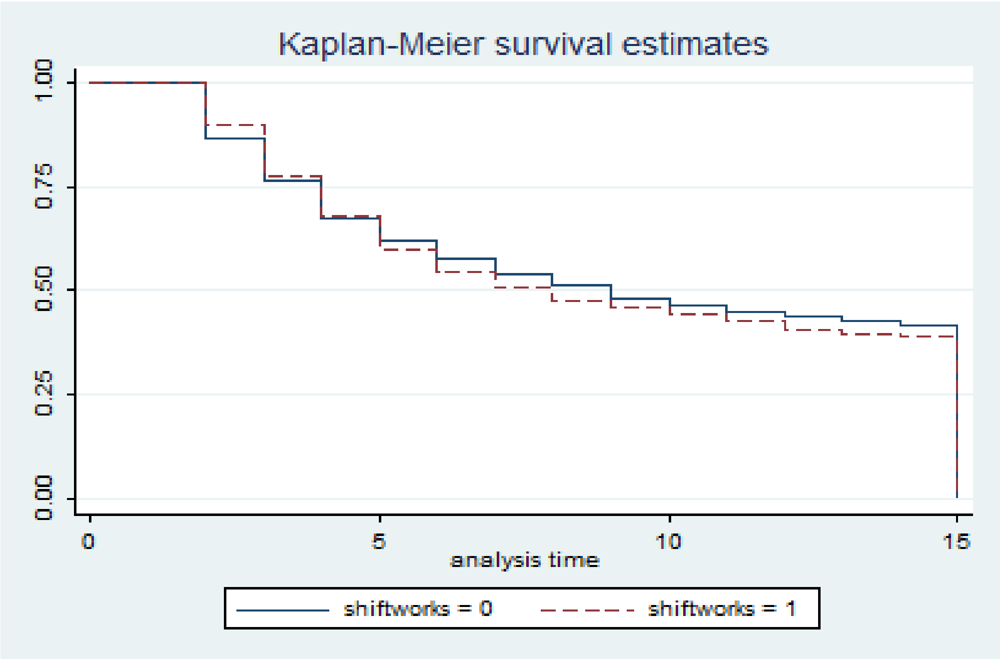
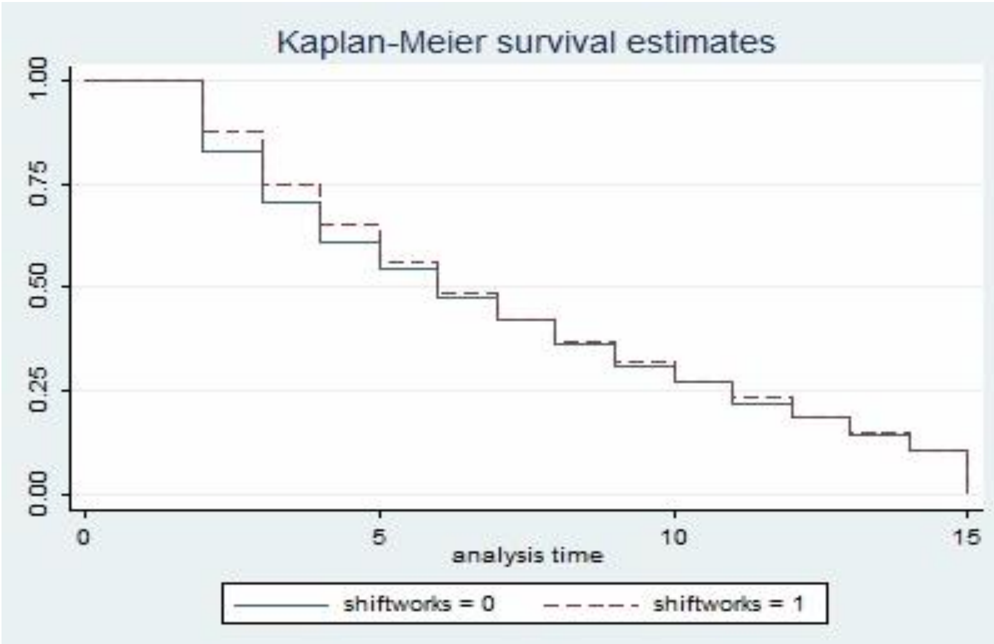


Figure 1.5-Survival Plots for Using Cocaine/Hard Drugs



B) Identification Strategy

i. Standard Panel Models

To examine how shift work affects individuals' substance use, I first present estimates from standard panel data models with different specifications. Linear probability estimates are only used to fit the baseline linear regression which is beneficial for comparison with the evidence from the previous literature. The baseline model has the following form:

$$\textbf{(1)}\ \boldsymbol{Y_{it} = \alpha + \beta Shift_{it} + X_{it}\gamma + u_{it}}$$

Y_{it} is the dependent variable for individual i at time t and represents a dummy indicating whether there was at least one day in the past month on which the individual consumed any type of substances. For cocaine/hard drugs this dummy variable is equal to one if the use occurred at least once in the past year. $\boldsymbol{Shift_{it}}$ is a binary variable equal to one if an individual experienced any

type of nonstandard work schedules in the past year. $\boldsymbol{X_{it}}$ is a vector of individual characteristics. It contains controls for ethnicity, age, education, log of income, general health, marital status, region, student status, living in an urban area and household size. I include the log of annual income since illicit drugs are not inexpensive goods and might be bought and used by people who earn more. Education might make people aware of substance hazards and convince them that they should alter their behavior, or it may be a proxy for time-or risk- preference parameters that may predict substance use. A dummy is also included to control for general health status since substance use could be a response to poor health conditions. Marital status and household size might play a role, first due to the economic burden that they impose and second due to the potential psychological impacts on the employees.

Of course, by estimating the linear probability model we run the risk of neglecting the unobserved individual characteristics that are hidden in the error term $\boldsymbol{u_{it}}$ and might be correlated with the explanatory variables. In order to factor out the effect of permanent unobserved heterogeneity across the individuals, I estimate a series of fixed effects specifications as follows:

$$\textbf{(2)}\ \boldsymbol{Y_{it} = \alpha_i + \beta Shift_{it} + X_{it}\gamma + \delta_t + u_{it}}$$

Where the definitions of the dependent, independent and control variables are essentially the same as the linear probability model and $\boldsymbol{\alpha_i}$ is the individual specific fixed effects. I also include $\boldsymbol{\delta_t}$ which is a vector of year fixed effects. Such year fixed effects can capture time specific shocks and trends pertaining to the use or availability of different substances.

In addition to the above specifications, I also estimate a set of Poisson models to account for the effect of shift work on substance use at the intensive margin as per following (Greene, 2007):

$$\textbf{(3)}\ \boldsymbol{E(Y_{it}|X_{it}, u_{it}) = \mathbf{exp}\,(\alpha_i + \beta Shift_{it} + X_{it}\gamma + u_{it})}$$

The count variable in these models is the number of days in the past month of the interview that the respondent drank, binge drank, smoked or used marijuana. For cocaine/hard drugs it is the number of times that the individual used the drug in the past year. It should be noted that the coefficients from these regressions should be interpreted differently from the previous section. For instance, the males' drinking coefficient of -0.143 means if a male respondent switches from a regular day schedule to any type of nonstandard schedule, the log of the expected number of the days he drinks goes down by 0.143, given the other predictor variables in the model are held constant. To account for individual heterogeneity, these models will also be estimated with a fixed effects specification.

ii. Survival Analysis Framework

Based on the medical evidence presented earlier, the linkage between shift work and substance use does not happen instantly and therefore time plays a crucial role that might be better captured by a duration framework. Thus, this study supplements standard panel techniques by conducting survival analyses. The key treatment variable here is a dummy for shift work. Survival times t in this paper are defined as spells of time (the number of years) that respondents do not use any substances, so the event of interest that ends these spells is the onset of use. To consider the effect of incomplete spells, the analysis accounts for right-censoring.

Cox's (1972) proportional hazards semiparametric method is used. This method presents the probability of the onset of using any substance during a given period, provided that the individual has not done it before. Hence, the estimated coefficients are proportional effects on the hazard ratios. Specifically, the model estimated has the following form:

$$\textbf{(4)}\ \lambda(t|X) = \lambda_0(t)\exp(\beta' x) \quad t=\text{survival times (spells)}$$

The baseline hazard function denoted as $\lambda_0(t)$ describes how the risk of the onset of using any substances per year changes over time at baseline levels of covariates. The effect parameters, exp (β'X), describe how the hazard rates vary proportionally in response to changes in the explanatory covariates. The shift work dummy acts as the main independent variable here. The reference group contains everyone employed in the past year and always working at a regular day schedule. The X vector in equation (4) contains the same set of controls as the earlier models. Moreover, in order to partially account for the unobserved heterogeneity, frailty adjustments will also be conducted. These adjustments take account of hidden heterogeneity or frailty in assessing the survival chances of individuals and are essentially the equivalent of random effects models in the regular panel specifications (Vaupel et al., 1979; Yashin et al., 2001).

IV. Empirical Results

A) Linear Probability and Fixed Effects Estimates

Table 1.5 reports the regression results on self-reported substance use. In this and the following tables, different rows demonstrate shift work coefficients from separate regressions for different substances.

Table 1.5- Linear Probability and Fixed Effects Estimates (with Industry Effects)

A. Type of Substance Use (Males)	**(LP)**	**(FE)**	**(LP*)**	**(FE*)**
Drinking	-0.058	-0.068	-0.061	-0.072
	(6.68)**	(9.39)**	(9.09)**	(9.05)**
Binge Drinking	-0.040	-0.024	-0.029	-0.023
	(3.20)**	(3.21)**	(3.08)**	(2.82)**
Smoking	-0.006	-0.002	-0.005	-0.002
	(0.69)	(0.45)	(0.53)	(0.34)
Using Marijuana	0.006	0.013	0.003	0.014
	(0.75)	(2.20)*	(0.44)	(2.27)*
Using Cocaine/Hard Drugs	0.014	0.012	0.012	0.010
	(3.37)**	(3.27)**	(3.11)**	(2.82)**

Industry Dummies*	No	No	Yes	Yes
B. Type of Substance Use (Females)				
Drinking	-0.018	-0.041	-0.019	-0.052
	(2.19)*	(5.77)**	(2.32)*	(6.81)**
Binge Drinking	0.016	0.003	0.011	-0.005
	(2.00)*	(0.06)	(1.48)	(0.84)
Smoking	0.043	0.027	0.044	0.021
	(5.33)**	(4.70)**	(5.06)**	(3.72)**
Using Marijuana	0.036	0.022	0.033	0.016
	(4.84)**	(4.57)**	(5.22)**	(3.12)**
Using Cocaine/Hard Drugs	0.024	0.018	0.023	0.015
	(6.61)**	(5.87)**	(6.48)**	(4.43)**
Industry Dummies*	No	No	Yes	Yes

Notes: Each row is from a separate regression for each substance and the reported are the linear probability (LP) and fixed effects (FE) estimates. Columns titled (LP*) and (FE*) present similar estimates from the specification that includes additional industry variables. T-statistics are in parentheses and are calculated after clustering the standard errors for the individuals.
*** Significant at the 1 percent level
** Significant at the 5 percent level   * Significant at the 10 percent level

The basic linear probability results in column LP suggest a negative correlation between shift work and drinking for both sexes, although the estimate for women is smaller and only marginally significant. For binge drinking, there is a small positive coefficient for female shift workers, whereas for male shift workers a negative correlation is observed. In the case of smoking, while there is a negative but statistically insignificant correlation for males, females show a positive and statistically significant relationship. For marijuana and cocaine/hard drugs both males and females demonstrate positive correlations.

Column FE of Table 1.5 presents the results of basic fixed effects estimates. The negative relationship between shift work and drinking becomes statistically more significant for both males and females. Interestingly, female shift workers who were shown in column LP to be associated with more binge drinking, indicate a smaller positive and statistically insignificant coefficient in this case. In general, accounting for individual fixed effects makes the shift work coefficients more negative or less positive than in column LP. This suggests shift workers seem to be more prone to substance use even if they were not doing shift work.

Columns LP* and FE* in Table 1.5 respectively report linear probability and fixed effects estimates after the inclusion of industry effects. This is an attempt to add to the homogeneity of the study sample. However, as emphasized by (Härmä 1993) and Saksvik et al. (2011), controlling for any job characteristics might also only come at the cost of preventing health from acting as a mediator.

Nonetheless, similar to what Ulker (2006) suggests, I find that the inclusion of industry effects does not critically change the coefficients and thus original conclusions remain broadly the same.

Although the focus of this study is to compare the substance use of shift workers and regular day workers and thus shift work is the main independent variable, it might be interesting to report some other covariates' results as well. Thus Appendix A presents the basic linear probability coefficients of the other independent variables. The results show that overall being married, having larger households, being in general good health, living in non-urban areas and having lower incomes is associated with lower substance use. Education does not play any significant role in regard to drinking, but smoking and using drugs are generally negatively associated with higher education. Non-Blacks also use more substances in general. Moreover, other than the case of smoking, the average effect of age on substance use is statistically insignificant. In addition, it seems shift workers living in the South or North Central parts of the country consume less substance compared to people living in the North East. Moreover, students drink more and use more drugs but smoke less compared to non-students. These general conclusions remain systematically the same across different specifications.

Table 1.6 presents the same estimates but after including a new variable that controls for the interaction of shift work dummy and total hours that an individual worked in the past year. Since

Trinkoff and Storr (1998) claimed that the effect of shift work increases with exposure, I include this variable to partially capture that. The marginal effects of the linear probability and fixed effects specifications reported in columns titled ME indicate that drinking and binge drinking are still negatively associated with shift work for males, but females who demonstrate a positive and significant correlation with binge drinking under the linear probability specification, show a much smaller and insignificant correlation under the fixed effects specification. Other coefficients do not show any major change.

Table 1.6- Linear Probability, Fixed Effects and Marginal Effects Estimates (with Total Hours Worked Interactions)

A. Type of Substance Use (Males)	**(LP)**	**(INT)**	**(ME)**	**(FE)**	**(INT)**	**(ME)**
Drinking	-0.177	0.00006	- 0.054	-0.213	0.00008	-0.061
	(11.87)**	(9.43)**	(6.14)**	(14.60)**	(12.01)**	(7.67)**
Binge	-0.011	0.00005	-0.028	-0.109	0.00005	-0.015
Drinking	(7.29)**	(7.82)**	(2.89)**	(7.93)**	(8.02)**	(1.81)*
Smoking	-0.019	0.00007	-0.006	-0.029	0.00001	0.0003
	(1.43)	(1.17)	(0.61)	(2.69)**	(3.34)**	(0.05)
Using	0.049	-0.00002	0.004	0.017	0.00004	0.012
Marijuana	(4.55)**	(6.02)**	(0.57)	(2.01)*	(0.11)	(2.05)**
Using	0.029	0.00008	0.013	0.016	-0.00002	0.011
Cocaine/Hard Drugs	(4.78)**	(3.44)**	(3.33)**	(2.68)*	(1.12)	(2.85)**
B. Type of Substance Use (Females)						
Drinking	-0.140	0.00008	-0.038	-0.017	0.00008	-0.042
	(10.79)**	(12.08)**	(4.72)**	(13.45)**	(12.59)**	(5.42)**
Binge	-0.056	0.00004	0.022	-0.068	0.00004	0.0007
Drinking	(4.84)**	(6.11)**	(2.76)**	(6.27)**	(7.44)**	(0.11)
Smoking	0.007	0.00002	0.050	-0.006	0.00002	0.025
	(0.56)	(4.05)**	(5.57)**	(0.65)	(3.72)**	(4.22)**
Using	0.029	0.00002	0.036	0.019	-0.00003	0.017
Marijuana	(3.02)**	(0.89)	(5.52)**	(2.03)*	(1.02)	(3.32)**
Using	0.025	0.00002	0.023	0.011	0.00002	0.015
Cocaine/Hard Drugs	(4.26)**	(0.34)	(6.49)**	(1.94)*	(0.94)	(4.50)**

Notes: The reported are coefficients from the linear probability and fixed effects specifications and each row is from a separate regression for each substance. Columns titled INT report the coefficients of the interaction between shift work and total hours worked in the past year. Columns titled ME report the marginal effects. T-statistics are in parentheses and are calculated after clustering the standard errors for the individuals.
*** Significant at the 1 percent level ** Significant at the 5 percent level * Significant at the 10 percent level

To partially account for the effect of long exposure to shift work, in a separate setting, I include an additional variable controlling for the interaction of cumulative amount of shift work and shift work itself. As shown in Table 1.7, the direction and significance of the results essentially remain about the same.

Table 1.7- Linear Probability, Fixed Effects and Marginal Effects Estimates (with Cumulative Amount of Shift work Effect)

A. Type of Substance Use (Males)	**(LP)**	**(INT)**	**(ME)**	**(FE)**	**(INT)**	**(ME)**
Drinking	-0.117	0.008	-0.073	-0.145	0.013	-0.073
	(7.83)**	(3.89)**	(8.77)**	(8.19)**	(4.70)**	(9.30)**
Binge Drinking	-0.052	0.003	-0.036	-0.075	0.009	-0.023
	(3.13)**	(1.18)	(4.08)**	(4.18)**	(3.27)**	(2.84)**
Smoking	0.063	-0.009	0.010	-0.002	0.000	-0.001
	(3.81)**	(3.76)**	(1.22)	(0.20)	(0.10)	(0.27)
Using Marijuana	0.046	-0.005	0.016	0.026	-0.002	0.013
	(3.54)**	(2.96)**	(2.21)**	(1.87)*	(1.16)	(2.11)**
Using Cocaine/Hard Drugs	0.009	0.000	0.012	0.009	0.000	0.010
	(1.27)	(0.49)	(3.31)**	(1.05)	(0.19)	(2.73)*
B. Type of Substance Use (Females)						
Drinking	-0.108	0 .012	-0.038	-0.118	0.012	-0.052
	(7.19)**	(5.97)**	(4.72)**	(6.44)**	(4.14)**	(6.80)**
Binge Drinking	-0.041	0.008	0.003	-0.043	0.006	-0.006
	(2.80)**	(3.56)**	(0.46)	(2.81)**	(2.67)**	(0.90)
Smoking	0.025	0.003	0.042	0.018	0.000	0.022
	(1.42)	(1.08)	(5.63)**	(1.36)	(0.33)	(3.74)**
Using Marijuana	0.017	0.002	0.032	0.022	-0.001	0.016
	(1.36)	(1.32)	(5.62)**	(1.91)*	(0.57)	(3.23)**
Using Cocaine/Hard Drugs	0.015	0.001	0.022	0.024	-0.001	0.015
	(2.16)**	(1.00)	(6.72)**	(3.16)**	(1.28)**	(4.48)**

Notes: The reported are coefficients from the linear probability and fixed effects specifications and each row is from a separate regression for each substance. Columns INT report the coefficients of the interaction between shift work and cumulative amount of shift work. Columns ME report the marginal effects. T-statistics are in parentheses and are calculated after clustering the standard errors for the individuals.
*** Significant at the 1 percent level
** Significant at the 5 percent level
* Significant at the 10 percent level

Although the results in this section provide the main foundation for the statistical analysis in this study, it would be more interesting to examine how shift work changes not only the average tendency to use these substances but also the intensity of use. Hence, the following section will provide the results of Poisson and fixed effects Poisson specifications.

B) Poisson Panel Estimates

Table 1.8 presents Poisson and fixed effects Poisson estimates. The main independent variable of these regressions is the same dummy as previous sections controlling for employment at any type of nonstandard schedules, but the dependent variable counts the number of days that the respondents reported using any of these substances within the past month of the interview. For the case of cocaine/hard drugs, the dependent variable counts the number of times that the respondent reported any use within the whole past year of the interview.

Table 1.8- Poisson and Fixed Effects Poisson Estimates

A. Type of Substance Use (Males)	**(PP)**	**(FE)**
Drinking	-0.148 (5.59)***	-0.152 (3.42)***
Binge Drinking	-0.121 (3.21)**	-0.083 (6.79)***
Smoking	0.022 (0.95)	-0.037 (5.71)***
Using Marijuana	-0.038 (0.64)	0.011 (0.99)
Using Cocaine/Hard Drugs	0.369 (2.16)**	0.249 (3.39)***

B. Type of Substance Use (Females)		
Drinking	-0.034 (2.46)**	0.085 (4.74)***
Binge Drinking	0.189 (3.94)***	0.035 (2.32)**
Smoking	0.037 (1.55)	0.035 (4.94)***
Using Marijuana	0.269 (3.27)***	0.006 (0.39)
Using Cocaine/Hard Drugs	0.692 (2.22)***	0.773 (3.68)***

Notes: Each row is from a separate regression and the reported are coefficients from Poisson, and fixed effects Poisson (FE) estimations, respectively. T-statistics are in parentheses and are calculated after jackknifing the standard errors for the individuals.
*** Significant at the 1 percent level
** Significant at the 5 percent level
* Significant at the 10 percent

Column PP in Table 1.8 exhibits pooled Poisson estimates. The coefficients for drinking and binge drinking are negative and significant for males. While women indicate negative associations with drinking, in the case of binge drinking, they show a positive and statistically significant correlation under the pooled specification. However, once individual permanent effects are taken into account in column FE, the coefficients become statistically insignificant. The intensity of smoking for male shift workers is not different from regular day workers, but females show positive coefficients. In the case of marijuana and cocaine/hard drugs, according to the fixed effects estimates in column FE, the intensity of use is higher for both male and female shift workers although males' marijuana coefficients are statistically insignificant.

C) Hazard Rate Estimates

As shown in column 1 of Table 1.9, the hazard ratio for the onset of drinking for male shift workers is 0.962 of that of the regular day workers; that is, almost a 4 percent decrease in the probability of the onset of drinking after controlling for other factors in the model. Likewise, there is a 4 percent decrease in the probability of the onset of binge drinking for male shift workers. Other than the cases of marijuana use and smoking for women, substances do not show a statistically significant decrease or increase in the risk of the onset of use, suggesting no differences in survival times.

Table 1.9- Cox Proportional Hazards Estimates with Frailty Corrections

A. Type of Substance Use (Males)	**(Cox Hazard Ratios)**	**(Cox Hazard Ratios with Frailty)**
Drinking	0. 962 (3.09)**	0.961 (3.13)**
Binge Drinking	0.961 (0.62)	0.960 (0.39)
Smoking	0.988 (0.26)	0.976 (1.00)
Using Marijuana	0. 971 (0.75)	0.969 (0.68)
Using Cocaine/Hard Drugs	1.038 (0.37)	1.007 (0.88)
B. Type of Substance Use (Females)		
Drinking	0.971 (0.20)	0.978 (0.70)
Binge Drinking	1.014 (0.29)	1.044 (1.72)

Smoking	1.068 (1.65)*	1.052 (1.29)
Using Marijuana	1.090 (2.52)**	0.143 (3.12)**
Using Cocaine/Hard Drugs	1.000 (0.02)	0.997 (0.13)

Notes: The main independent variable is a dummy controlling for individuals who have experienced shift work for some time within the past year. The numbers in parenthesis are t-statistics. Standard errors have been clustered for individuals.
*** Significant at the 1 percent level
** Significant at the 5 percent level
* Significant at the 10 percent level

To partially target the unobserved heterogeneity of the baseline Cox model, I also present estimates with frailty corrections. Nonetheless, the risk of the onset of drinking and binge drinking still remains lower for shift workers against regular day workers and most other hazard ratios do not show any statistically significant difference across the two groups.

V. Concluding Remarks

The increasingly competitive nature of the 24 hour society has given rise to a multitude of employment types and work schedules. Nonstandard work schedules can disrupt circadian rhythms that some researchers have suspected to trigger heavier drinking habits or cause an increase in drug use. This study has investigated that hypothesis using data from rounds 1 to 15 of the NLSY97. The identification strategy relies on several panel specifications at the extensive and intensive margins as well as hazard regressions.

My results indicate that holding a job with any type of nonstandard schedule is negatively correlated with regular drinking or binge drinking for both men and women. Evidence is only slightly more consistent with the proposed hypothesis for smoking: men always show a small

negative correlation, though for women the estimates indicate a small positive correlation both at the intensive and extensive margins. On the other hand, shift work does appear to cause a modest increase in drug use for both men and women. It is noteworthy, however, that almost all coefficients are smaller for fixed effects estimations, consistent with the hypothesis that people prone to substance use are more likely to do shift work. Also, the negative influences of shift work appear to be larger for women than for men. These results are robust to alternative specifications such as including industry controls or interaction terms of cumulative amount of shift work and total hours worked in the past year with the shift work variable itself.

One promising topic for future research would be to conduct separate analyses on each type of nonstandard schedules to see if the results differ across the schedule types. Depending on the reasons that they affect substance abuse patterns, it may not be surprising if (e.g.) the frequent circadian adjustments necessitated by a rotating shift caused more substance abuse than would a regular night shift. Moreover, the use of a more representative sample of individuals that are not drawn from a specific age range could help us to draw better inferences about the general population—a potential concern if we believe that social influences or habituation caused the substance use decisions of younger workers to be more sensitive to their work schedules. Of course, testing such hypothesis would likely require a larger data sets than those currently available.

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Appendix

Baseline Linear Probability Estimates (with Main Demographics)

Main Demographics	Drinking	Binge Drinking	Smoking	Using Marijuana	Using Cocaine/Hard Drugs
Hispanic	0.094	0.138	0.057	-0.012	0.029
	(7.22)**	(11.40)**	(4.19)**	(1.33)	(6.94)**
Mixed Race	0.104	0.125	0.116	0.036	0.048
	(2.52)**	(2.84)**	(2.32)**	(1.05)	(2.38)**
Non-Black(Non-Hispanic)	0.184	0.211	0.164	0.041	0.053
	(17.36)**	(21.57)**	(14.32)**	(5.03)**	(15.38)**
Age	0.005	0.000	0.001	0.000	-0.003
	(0.81)	(0.41)	(3.07)**	(1.28)	(1.04)
North Central	0.009	-0.019	0.011	-0.014	-0.013
	(0.90)	(1.19)	(0.88)	(1.46)**	(2.66)**
South	-0.031	- 0.007	0.010	- 0.021	-0.001
	(3.10)**	(0.68)	(0.98)	(6.81)**	(0.24)
West	0.008	0.014	-0.028	0.011	0.011
	(0.73)	(1.15)	(2.28)**	(1.14)	(2.09)**
Household size	-0.005	-0.003	-0.003	-0.029	-0.002
	(3.45)**	(2.27)**	(1.73)	(2.82)**	(3.12)**
Associate and Bachelor's	0.030	-0.007	-0.062	- 0.017	-0.008
	(4.29)**	(1.01)	(10.74)**	(3.51)**	(2.46)**
Graduate degree	0.055	-0.012	-0.081	-0.017	-0.015
	(3.52)**	(0.73)	(6.55)**	(1.49)	(2.27)**
Professional Degree	0.080	-0.031	-0.084	-0.014	-0.027
	(1.59)	(0.82)	(2.60)**	(0.62)	(4.04)**
Married	-0.028	-0.034	-0.018	-0.018	-0.010
	(4.19**	(5.34)**	(3.41)**	(4.35)**	(3.87)**
Healthy	0.004	-0.010	-0.018	-0.006	-0.007
	(0.04)	(1.26)	(2.39)**	(0.97)	(1.71)*
Log(wage)	0.001	0.001	-0.003	0.000	0 .000
	(3.17)**	(2.14)**	(5.07)**	(0.12)	(1.41)
Urban	0.031	0.021	0.000	0.034	0.011
	(3.60)**	(2.36)**	(0.03)	(5.18)**	(3.53)**
Student	0.029	-0.026	-0.125	0.034	0.011
	(4.23)**	(3.78)**	(17.17)**	(5.18)**	(3.53)**

The excluded categories against which other indicators are measured include African-Americans (race/ethnicity), the Northeast region, and persons with no more than a high school education. T-statistics are in parentheses and are calculated after clustering the standard errors for the individuals.

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

Chapter 2- The Effect of Alcohol Consumption on Job Search Behavior:

A Regression Discontinuity Application of Minimum Drinking Age Laws

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Abstract

This paper investigates the effect of alcohol use on job search behavior of young individuals. Using the age of respondents from the NLSY97 both in the year and month formats and applying regression discontinuity design by utilizing the surge in alcohol consumption at age 21, I find that young adults tend to increase their drinking and binge drinking once they are allowed to legally access alcohol. However, I find that the surge in alcohol use at age 21 does not seem to immediately or directly affect the job search behavior of young individuals while they are employed or unemployed. I also find that it does not seem to affect their lack of desire for work.

Keywords: Minimum Drinking Age Laws, Alcohol, Drinking, Binge Drinking, Job Search

JEL Classification Codes: I12, I19, J22

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I. Introduction :

Alcohol use specifically at levels considered above moderate has been demonstrated to be associated with a number of adverse outcomes. A few studies have suggested that alcohol use might increase smoking and the marijuana or hard drug use (Deza, 2015; Yörük and Yörük, 2011), higher motor vehicle fatalities (Cook and Tauchen, 1984; Ruhm, 1996; Dee, 1999; Dee and Evans, 2001), more violence and accidents at work (Li and Bai, 2008), higher incidence of occupational injuries (Trent, 1991), significant reductions in academic performance (Carrell et al., 2011) and more frequent workplace absenteeism (Johansson et al., 2014; Bacharach et al., 2010).

Alcohol consumption is also thought to affect labor market outcomes such as wages (Berger and Leigh, 1988; Kenkel and Ribar 1994; Hamilton and Hamilton 1997; Zarkin et al. 1998), occupational attainment (McDonald and Shields, 2001) and work performance (Blum et al. 1993; Mangione et al., 1999) due to some physical, psychological and cognitive impairments that can happen in the short run or long run (NIAAA1994). Heavy drinking is particularly believed to cause "alcohol myopia", unusual or unstable behavior and violence in individuals. These direct adverse outcomes as well as some related secondary effects such as accidents, absenteeism, and divorce can affect a potential worker's employment, productivity, and behavior.

Although the literature has previously studied the relationship between drinking and unemployment (Arcaya et al., 2014; Mullahy and Sindelar 1996), this paper is the first to examine the effects of moderate and excessive drinking behaviors on the amount of job search efforts by young individuals. It is also particularly interested in finding a meaningful causal relationship since the previous studies have brought about the possibility of a reverse causality in the sense that the emotional and financial stress of remaining unemployed could make individuals abuse alcohol.

If more severe alcohol consumption caused a reduction in the intensity of job search, it could possibly create an additional burden on the society in terms of unemployment compensation and welfare benefits. To deter the potential unfavorable effects of alcohol consumption on the labor market, governments and social policy makers could modify the current alcohol policies or design different welfare compensation mechanisms for the unemployed who specifically face problem drinking.

In this paper I use twelve rounds of the NLSY97 and establish causality through a regression discontinuity design by utilizing the exogenous decrease in the cost of accessing alcohol at 21 (due to the MLDA[5] laws). I initially find that there is a surge in both moderate and excessive drinking when young individuals can legally start drinking. However, by applying parametric regression discontinuity techniques, I find that such surge does not have any significant impact on the intensity of job search by young individuals in the year prior to the time they were interviewed. The respondents' desire to work after this increase in alcohol consumption also remains broadly the same.

The rest of the paper is structured as follows. Section II explores the related literature. Section III discusses the data and methodology. Section IV presents the results, and Section V concludes.

II. Background :

Alcohol-related harms are broadly divided into individual and socioeconomic consequences. From a personal health perspective, alcohol has been associated with more than 200 hazardous conditions and risky behaviors, some of which can happen concurrently (WHO 1992a; Rehm et al.,

[5] Minimum Legal Drinking Age

2010a; Rehm et. al, 2012; Shield et al., 2013). From a socioeconomic standpoint, however, there are both tangible and intangible costs that are attributed to the moderate or excessive use of alcohol. Tangible costs range from those attributed to healthcare, legal and welfare systems that are directly borne by a society to lost productivity and working years, decreased earning potentials and higher unemployment rates that are more indirectly associated with alcohol use (Anderson et al., 2006; Thavorncharoensap, 2009).

Job search behavior, on the other hand, has often been regarded as a multidimensional construct (Kanfer et al., 2001; Van Hoye, 2013). This means its heterogeneity across the individuals can be analyzed from different perspectives. According to McCall (1970), other than the economic considerations and assessment of the value of foregoing alternatives, the psychic costs of looking also play a role in the "discouraged worker" phenomenon and prolonging the search process. Also, based on the simplest job search model in the economics literature, an individual stops searching when he receives a wage that is at least equal to his reservation wage. Of major less pecuniary factors that could alter the reservation wage are the marginal utility of leisure (Kasper, 1967), psychic and anxiety costs (Holt, 1970) and risk propensity (Harnett et al. 1971).

On the non-labor market side, as Carlier et al. (2014) discuss, a person's health as well as intentions and attitudes towards the search process, can affect the search behavior and re-employment. In addition, according to Kanfer et al. (2001), any search starts with the identification and commitment to an employment goal. Such commitment requires strong personality-motivational strengths to result in favorable employment outcomes.

Drinking, specifically at excessive levels could potentially impair an individual's cognitive abilities and thus assessment of costs of remaining unemployed and subsequently the reservation

wage. It can also affect a person's commitment to job search as goal. In addition, the well documented physical and psychological consequences of heavy alcohol consumption can also affect the job seeking behavior of the individuals.

While this study is the first attempt to model the potential unfavorable effect of alcohol on job search behavior using panel data, the dimensions that can be studied are limited. Although the data allows me to test the hypothesis for both employed and unemployed individuals, only the effort intensity and frequency of job search activities within the past year are tested. Overall, the results suggest that the increase in alcohol consumption (caused by an exogenous decrease in the cost of having access to alcohol) occurring at age 21 does not affect the intensity of job search behavior. In addition, as it is directly tested, the surge in alcohol consumption does not seem to directly affect the American young adults' desire to look for jobs.

III. Data and Methodology

A) Data and Descriptive Statistics

This study uses rounds 1-12 of the U.S. National Longitudinal Survey of Youth (NLSY 97), starting in 1997 and ending in 2008. This survey provides detailed annual information on regular and excessive drinking (which will hereafter be called "binge drinking") by asking the following questions: "During the last 30 days, on how many days did you have one or more drinks of an alcoholic beverage?" and "On how many days did you have five or more drinks on the same occasion during the past 30 days? By occasion we mean at the same time or within hours of each other. "

The intensity of job search has also been provided as the number of weeks within the past year that the individuals spent searching for jobs. This information is available for both individuals

who were already employed by an employer and still looked for other employment opportunities and those who did not even report doing any type of freelance jobs. The data further allows me to test whether the reason behind putting less effort into job seeking is unwillingness to work.

The advantage of this dataset for the purpose of the current study is investigating young adults who are at a critical age when they are making their very first career choices of their lives around the time of graduation from high school or college. These individuals are also more likely to drink, specifically when they become legally eligible. However, the drawback of this particular age group is the inability to generalize the overall findings for other age cohorts.

Round 1 of the survey starts with 8,984 individuals who were interviewed annually for 12 consecutive rounds. Table 2.1 presents descriptive statistics for drinking and well as job search behavior at ages 20, 21 and 22. It broadly indicates that when individuals become 21, all measures of alcohol consumption show a surge. To be more precise, the average number of days in the past month that an individual had at least one drink sharply increases from 3.51 days to 4.9 days whereas the same measure for binge drinking shows a jump from an average of 1.6 days to 2.03 days. In addition, the share of the days of the past month reported drinking indicates an increase from 11% to 16%. However, the job seeking behavior of the employed individuals does not show a significant change, but for people without any freelance opportunities, the frequency of behavior increases from an average search time of 5.36 weeks to an average of 5.84 weeks.

Table 2.1- Summary Statistics of the Main Variables at Age 20, 21 and 22

	Drinking	Binge Drinking	Share of Days Drinking Last Month	Job Search Employed	Job Search No Freelance
Number of Observations at 20	7820	7788	7820	5048	4601
Frequency of Behavior	3.515 (5.774)	1.616 (3.847)	0.117 (0.192)	0.256 (0.436)	5.361 (11.389)
Number of Observations at 21	7705	7667	7705	5320	4089
Frequency of Behavior	4.892 (6.667)	2.031 (4.304)	0.163 (0.222)	0.247 (0.431)	5.846 (11.44)
Number of Observations at 22	7671	7606	7671	5548	3932
Frequency of Behavior	4.608 (6.328)	1.802 (3.880)	0.153 (0.210)	0.257 (0.437)	5.943 (11.435)

The frequency of behavior for alcohol is the average number of days in the past month that the respondents reported consuming. For job search while employed the frequency is the probability that the individuals looked for jobs within the past year while they held an employee job. For job search with no freelance the frequency of behavior is the number of weeks in the past year spent looking for jobs. The figures in the parentheses report standard deviations.

B) Regression Discontinuity Design

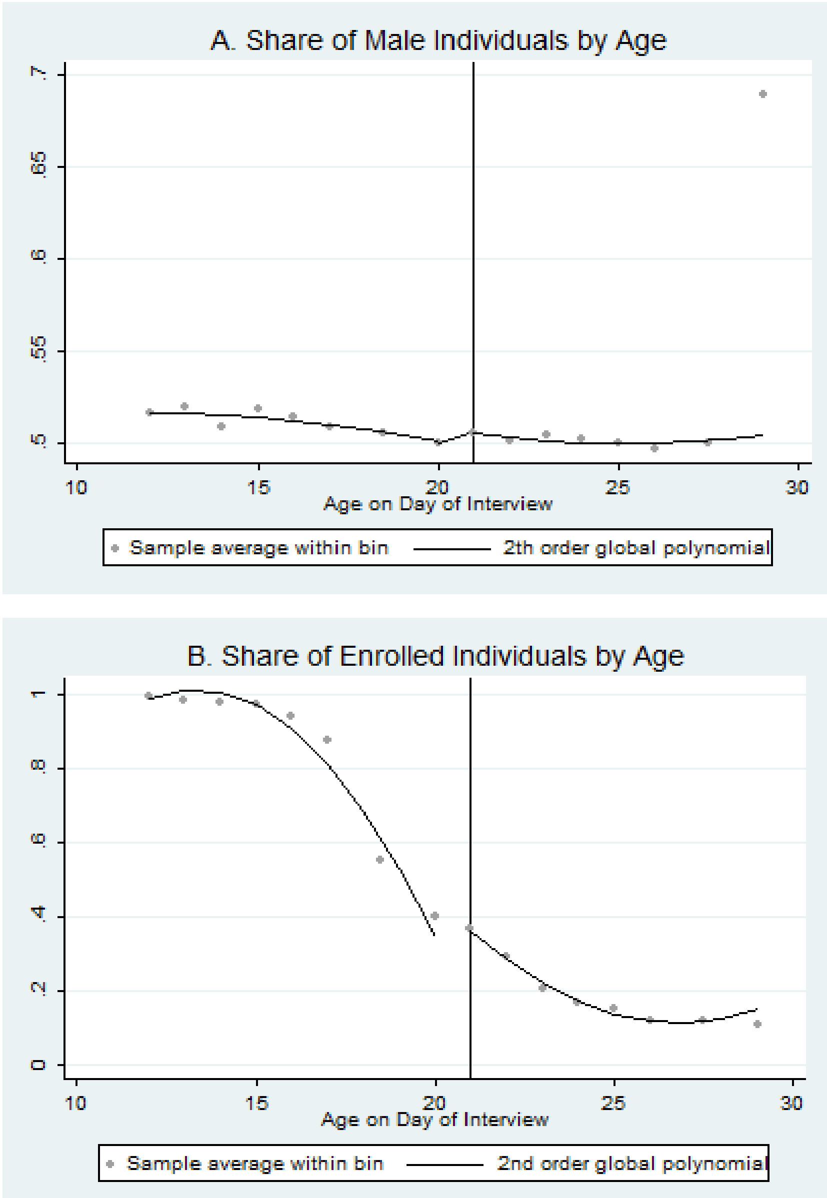
To examine how alcohol consumption affects individuals' job search behavior, I first use a regression discontinuity design to estimate the effect of MLDA laws on average regular drinking, binge drinking and the share of the days within the past month with any reported drinking behavior. Imbens and Lemieu (2008), Lee and Lemieux (2009) and Jacob and Zhu (2012) provide a thorough discussion of the RD design and a practical guide to it. The baseline RD regression model in my empirical analysis has the following form:

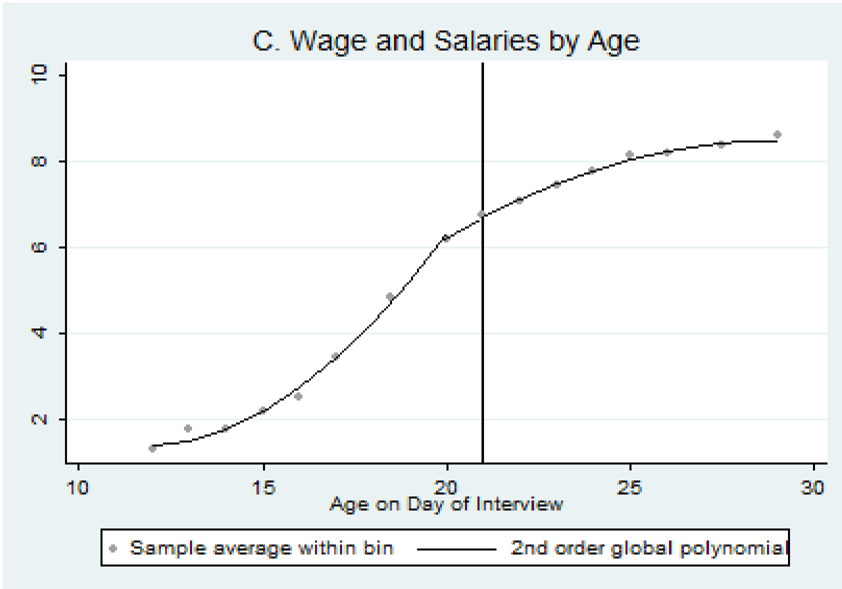
$$(5)\ \boldsymbol{Y_{it} = \gamma X_{it} + \delta T_i + \alpha f(ageindex_{it}) + u_{it}}$$

Where Y_{it} is the dependent variable for individual i at time t and represents the different measures of alcohol consumption within the past month. $\boldsymbol{X_{it}}$ is a matrix of individual characteristics. It includes controls for race of the respondent, age, education, log of income, marital status, region, enrollment status, living in an urban area and household size. I include the log of annual income since it indirectly affects the reservation wage of the respondents on the job search as well as how seriously they conduct their search follow-ups. Education and the degree that the respondents obtain is related to the intensity of job seeking behavior. Marital status and household size might play a role, first due to the economic burden that they impose and second due to the potential behavioral changes in the individuals. $\boldsymbol{T_{it}}$ is the treatment variable equal to 1 if the respondent is 21 or older at the interview time and 0 otherwise. Thus, $\boldsymbol{\delta}$ is the major coefficient of interest and demonstrates the causal effect of MLDA law on the outcomes.

The validity of any RD design and the resulting causal inferences rely on two major factors: First, none of the variables other than the forcing variable should indicate a jump at the cutoff point. As figures 2.1 and 2.2 suggest, this seems to be the case in this study. In those graphs, it is shown that major control variables (Share of male individuals, annual wages and salaries and share of enrolled individuals) that seem to play a role in the respondents' job seeking behavior are not associated with any sudden change.

Figure 2.1: Smooth Transition of Main Control Variables




C. Wage and Salaries by Age
10
8
6
4
2
10
15
20
25
30
Age on Day of Interview
Sample average within bin
2nd order global polynomial

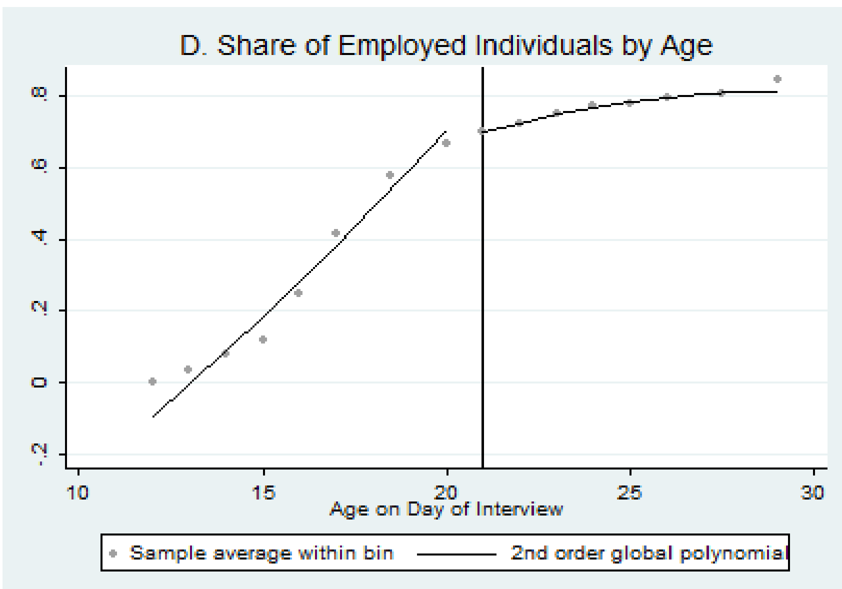
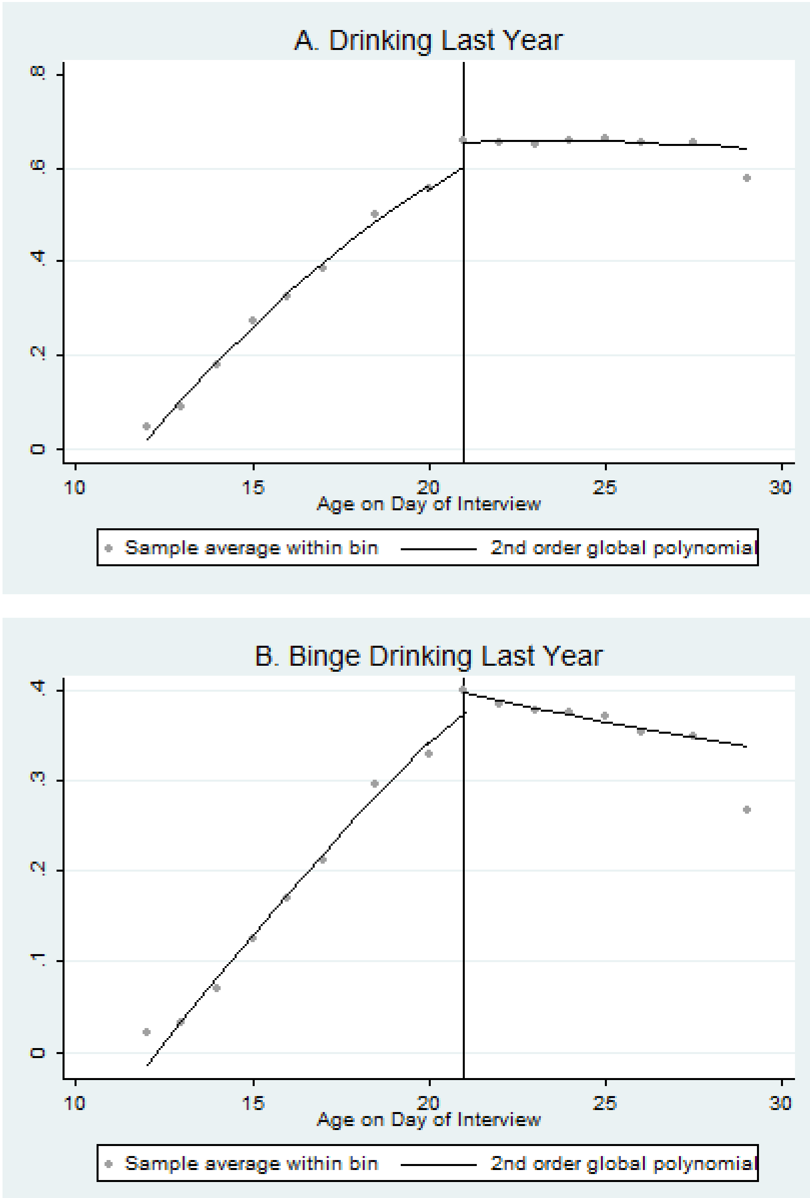
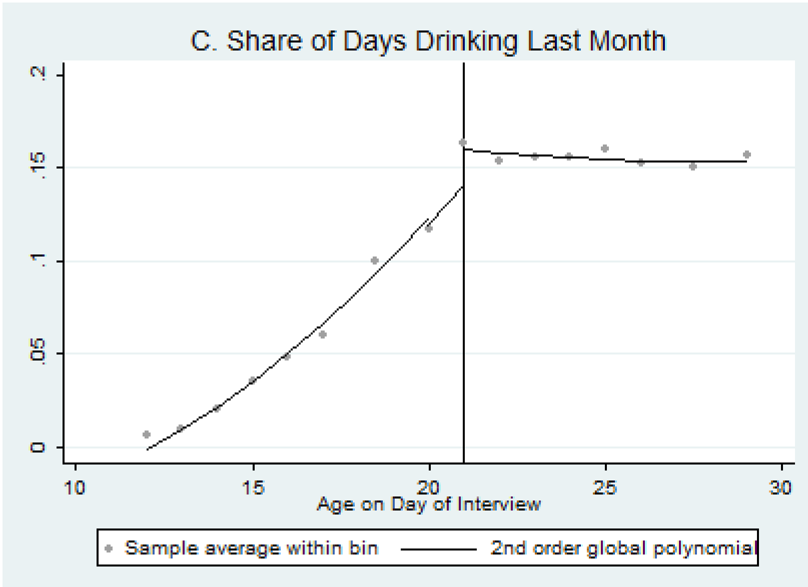
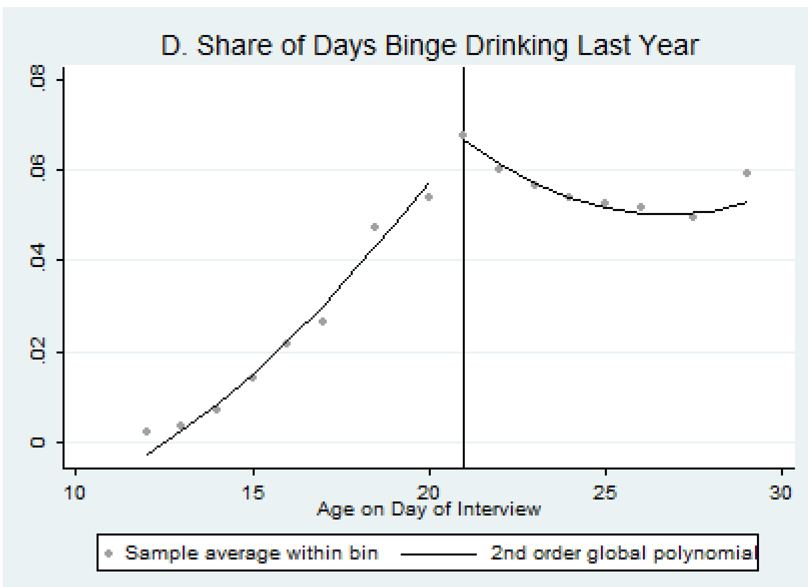

D. Share of Employed Individuals by Age
.8
.6
.4
.2
0
-.2
10
15
20
25
30
Age on Day of Interview
Sample average within bin
2nd order global polynomial

Figure 2.2: Alcohol Consumption by Age







However, in the case of enrolled and employed respondents, the transitions do not seem as smooth as the other demographic characteristics. Therefore, all estimations are conducted using age in a month format rather than a year format. This serves the purpose to be closer to the cutoff point.

Second major issue with the RD implementation is the choice of an appropriate functional form for the forcing variable. Nonetheless, according to Gelman and Imbens (2014), the use of higher order polynomial functional forms for the forcing variable is associated with three main unattractive features: Assigning higher than necessary weights to the outliers, risking a higher sensitivity of results

to the choice of the polynomial order and the hazard of over rejecting the null hypothesis. To minimize the risk of poor inferences due to misspecification of the regression model, I only consider linear and quadratic functions of age. Thus, my parametric models that include linear and quadratic interactions of age profile with the treatment can be shown as:

$$\textbf{(6)}\ \boldsymbol{Y_{it} = \gamma X_{it} + \delta T_i + \sum_{j=1}^{k} \alpha_j age_{it}^{j} + \sum_{j=1}^{k} \lambda_j (T_i \times age_{it}^{j}) + u_{it}} \qquad \boldsymbol{for\ k = \{2\}}$$

IV. Empirical Results

Table 2.2 reports the regression results on several alcohol consumption measures. The first two columns report the coefficients from regressions in which the dependent variables indicate the occurrence of regular and binge drinking at least once within the past month. The third and fourth columns report estimates from regressions whose dependent variables account for the share of days within the past month that an individual reported drinking or binge drinking. In the second half of the table, the results are presented for different subsamples that are essentially stratified according to the respondents' age difference from 252 months of age. The main reason behind this strategy is to recognize age groups that indicate a more significant surge in alcohol consumption. As results show, there does not seem to be a particularly interesting age category that should be focused on, thus all models will be estimated using age in a month format, but for the complete sample.

As it is clearly seen, all positive and statistically significant coefficients of the treatment variable are associated with a surge in alcohol consumption at age 252 months (21 years), confirming the effects of MLDA laws previously documented in the literature (Carpenter and Dobkin, 2009; Yörük and Yörük, 2011).

Table 2.2- The Effect of MLDA Law on Different Measures of Alcohol Consumption

Whole Sample	**Drinking**	**Binge Drinking**	**Share of Days Drinking**	**Share of Days Binge Drinking**
Treatment	0.0108	0.006	0.028	0.001
	(3.35)***	(2.16)**	(3.17)**	(1.72)*
Age index	-0.0008	-0.0006	0.000	-0.0001
	(3.06)***	(2.67)*	(1.55)	(2.42)**
Age index^2	0.00039	0.0002	0.000	0.0008
	(1.36)	(1.01)	(0.72)	(1.36)
Treatment	0.002	0.001	0.000	0.0003
× Age index	(6.99)***	(5.28)***	(1.32)	(3.51)***
Treatment	-0.00001	-0.00001	0.000	-0.0002
× Age index^2	(4.10)***	(3.44)***	(0.96)	(2.64)***
Year Fixed Effects	Yes	Yes	Yes	Yes
By Difference in age from 252 months old(Treatment)	**Drinking**	**Binge Drinking**	**Share of Days Drinking**	**Share of Days Binge Drinking**
2 Months	-0.013	0.006	0.004	0.007
	(0.69)	(0.32)	(0.59)	(1.60)
3 Months	-0.014	-0.005	0.002	0.003
	(0.89)	(0.38)	(0.33)	(1.03)
4 Months	-0.019	-0.0008	0.0005	0 .002
	(1.43)	(0.01)	(0.11)	(0.73)
6 Months	-0.012	0.007	-0.0006	0.006
	(1.11)	(0.67)	(0.14)	(0.26)
8 Months	0.003	0.011	0.001	0.0006
	(1.10)	(1.35)	(0.39)	(0.29)
Year Fixed Effects	Yes	Yes	Yes	Yes

Notes: T-statistics are in parentheses and are calculated after clustering the standard errors for the individuals.
*** Significant at the 1 percent level
** Significant at the 5 percent level
* Significant at the 10 percent level

Table 2.3 reports the occurrence of job search among the respondents who were already working for an employer within the past year. I also follow the previous strategy and include only quadratic polynomials of the age function in the regressions as well as the interactions with the treatment variable. Moreover, I report the effects for students and non-students separately to determine if any significant differences exist between the two groups regarding their job search behavior.

Table 2.3- The Job Search Behavior Model (with an Employer)

	Job Search		
Not Enrolled	**(1)**	**(2)**	**(3)**
Treatment	0.009	0.006	0.003
	(1.91)*	(1.25)	(0.62)
Age index	0.000	0.000	0.000
	(3.88)**	(3.69)**	(3.62)**
Age index^2	0.000	-0.000	-0.000
	(0.30)	(1.15)	(0.15)
Treatment $\times$ Age index	0.016	0.000	-0.000
	(0.06)	(1.46)	(1.51)
Treatment $\times$ Age index^2	0.000	0.001	0.000
	(1.60)	(0.78)	(0.81)
Controls	No	Yes	Yes
Year Effects	No	No	Yes
Enrolled			
Treatment	0.015	0.016	0.014
	(2.38)**	(2.28)**	(2.03)**
Age index	0.0002	0.000	- 0.000
	(0.50)	(0.29)	(0.17)
Age index^2	0.000	0.000	0.000
	(0.44)	(0.34)	(0.44)
Treatment $\times$ Age index	0.000	0.028	0.006
	(0.08)	(0.10)	(0.08)
Treatment $\times$ Age index^2	0.000	0.000	0.000
	(0.09)	(0.24)	(0.90)
Controls	No	Yes	Yes
Year Effects	No	No	Yes

Notes: Treatment is a dummy which is equal to one if the respondent is 21 years or older. Age index is the difference between the respondents' age and age 252 months. Column 1 reports the baseline model whereas columns 2 and 3 report the estimates after the inclusion of controls and year effects respectively. T-statistics are in parentheses and are calculated after clustering the standard errors for the individuals.
.*** Significant at the 1 percent level** Significant at the 5 percent level * Significant at the 10 percent level

As it is shown in column 1 of the table, the coefficient of the treatment variable is positive which essentially means both the enrolled and non-enrolled individuals who are 21 and older are more likely to search for jobs even when they are holding a job. However, these coefficients are more statistically significant for enrolled students implying a more noticeable change in their job search. Furthermore, columns 2 and 3 report the same procedure with the inclusion of control variables and year effects which do not change the initial inferences and the general pattern of the estimates remain broadly the same.

Table 2.4 presents the results of similar regressions for respondents who are neither working for an employer nor holding a freelance job. The dependent variable in these regressions accounts for the intensity of job search efforts given as the number of (unemployed) weeks spent searching for jobs in the past year. These estimates suggest insignificant change in job search behavior for non- students whereas students show positive and statistically significant correlations. Also, control variables and year effects do not significantly change the results.

Table 2.4- Job Search Behavior Model (without Freelance Jobs)

Not Enrolled	**(1)**	**(2)**	**(3)**
Treatment	-0.137	-0.018	0.551
	(1.42)	(0.18)	(1.18)
Age index	-0.003	0.001	-0.001
	(1.46)	(0.26)	(0.21)
Age index^2	-0.0002	-0.0003	0.0004
	(0.03)	(0.36)	(0.97)
Treatment	-0.0001	-0.001	-0.0003
$\times$ Age index	(0.30)	(0.17)	(0.08)
Treatment	0.0002	-0.0001	0.0002
$\times$ Age index^2	(0.27)	(0.33)	(0.60)
Controls	No	Yes	Yes
Year Effects	No	No	Yes
Enrolled			
Treatment	0.175	0.265	0.387
	(2.46)**	(3.44)**	(5.09)***
Age index	-0.003	0.002	0.017
	(2.25)**	(0.48)	(3.66)***
Age index^2	- 0.002	-0.0003	- 0.0001
	(0.69)	(0.77)	(3.76)
Treatment	0.0001	0.060	-0.009
$\times$ Age index	(0.22)	(8.21)***	(1.13)
Treatment	0.029	-0.0005	0.0001
$\times$ Age index^2	(1.13)	(5.39)***	(1.28)
Controls	No	Yes	Yes
Year Effects	No	No	Yes

Notes: Treatment is a dummy which is equal to one if the respondent is 21 years or older. Age index is the difference between the respondents' age and age 252 months. Column 1 reports the baseline model whereas columns 2 and 3 report the estimates after the inclusion of controls and year effects respectively. T-statistics are in parentheses and are calculated after clustering the standard errors for the individuals.*** Significant at the 1 percent level** Significant at the 5 percent level * Significant at the 10 percent level

Table 2.5 does a deeper analysis and restricts the sample to the individuals who did not try looking for jobs while being unemployed. They were further asked why they did not seek jobs and

in this section we are interested only in those who lacked the desire for work at the time of the interview. This is directly related to Kanfer et al. (2001) in the sense that any job search effort starts with identifying an employment goal. Since the individuals who are less willing or not willing to work are less likely to have a clear definition of their future career goals, it can be assumed that they are also less likely to search for jobs.

Table 2.5- The Model for Lack of Desire for Work

Not Enrolled	**(1)**	**(2)**	**(3)**
Treatment	-0.009	-0.007	-0.013
	(1.34)	(1.17)	(1.69)*
Age index	0.001	0.001	0.0007
	(3.35)***	(3.51)***	(1.05)
Age index^2	-0.0004	-0.0001	0.0006
	(3.69)***	(2.81)***	(0.83)
Treatment	-0.0004	-0.0001	-0.0003
$\times$ Age index	(3.30)***	(2.78)**	(0.50)
Treatment	0.001	-0.0001	0.0003
$\times$ Age index^2	(4.23)***	(1.69)*	(0.03)
Controls	No	Yes	Yes
Year Effects	No	No	Yes
Enrolled			
Treatment	0.010	0.011	0.003
	(1.85)*	(1.80)*	(0.75)
Age index	0.001	0.001	0.0001
	(4.29)***	(3.48)***	(0.40)
Age index^2	-0.0006	-0.0001	0.0005
	(1.55)	(2.77)***	(0.13)
Treatment	-0.0007	-0.0007	-0.0001
$\times$ Age index	(2.97)**	(2.51)**	(2.08)**
Treatment	0.0001	0.0007	0.0008
$\times$ Age index^2	(1.10)	(0.98)	(1.28)
Controls	No	Yes	Yes
Year Effects	No	No	Yes

Notes: Treatment is a dummy which is equal to one if the respondent is 21 years or older. Age index is the difference between the respondents' age and age 252 months. Column 1 reports the baseline model whereas columns 2 and 3 report the estimates after the inclusion of controls and year effects respectively. T-statistics are in parentheses and are calculated after clustering the standard errors for the individuals.
*** Significant at the 1 percent level
** Significant at the 5 percent level
* Significant at the 10 percent level

Results from table suggest that at age 21 or 252 months, individuals do not seem to show any significantly change in their desire for work that might have been triggered by a surge in alcohol consumption and its potential harmful impacts.

V. Concluding Remarks

Alcohol consumption has often been associated with various negative physical and psychological health impacts. This study has made an attempt to study the causal effect of alcohol consumption on job search behavior by testing the impact of the MLDA laws on several measures of job search behavior using a regression discontinuity approach utilizing the exogenous surge in alcohol consumption at age 21. Although the effects of the MLDA laws on alcohol consumption and the related outcomes can be found in several studies, few have looked at this exogenous increase in alcohol consumption and none have considered the possible spillover effects on the job search behavior of the individuals. In this study, such effects are measured using data from rounds 1 to 12 of the NLSY97.

To confirm the validity of the regression discontinuity design, it is initially shown that the main observable characteristics have a relatively smooth transition around age 21. To see the more precise immediate impact of the MLDA laws on alcohol consumption, all models use age in a month format. Estimates solidly suggest that different measures of alcohol consumption indicate a significant increase once respondents become 21. However, this significant surge does not have any statistically significant immediate impact on the occurrence of additional job search for the respondents who reported already working for an employer. The MLDA laws also do not seem to have any significant impact on the intensity of job search by the respondents who neither had an employer nor held any freelance jobs. Finally, it shown that the MLDA laws and the jump in alcohol consumption do not generally change the individuals' desire for work.

Although this study is the first to examine the effect of alcohol consumption on job search behavior using a regression discontinuity design, it should be noted that the concluding inferences

can only be made for this specific age range and further claims regarding the impacts of alcohol limiting policies need deeper investigation. In addition, job search is a multidimensional construct, but in this study I could only look at the individuals' self-reported intensity of job search and their desire for work. Future work can look at the methods that individuals use for these efforts and their future labor market outcomes. A future study will also require a more thorough source of data with alcohol consumption and job search variables that better match in terms of timing. Finally, other empirical methods such as events studies or instrumental variable approach can also be used to make plausible causal inference regarding the impact of moderate or excessive drinking on the job search behavior of the individuals.

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Chapter 3- The Supervisor-Subordinate Demographic Congruence and Employees' Mental Health

Mona Khadem Sameni*

June 2016

Abstract

This paper investigates the effects of workers' age, gender, and race relative to those of their supervisors on several measures of the employees' mental wellbeing. Evidence suggests that men show positive mental health signs when they have supervisors of same gender and race. They also seem to like supervisors who are almost the same age. On the contrary, women's mental health seems to be negatively affected when they have female supervisors. When the gender match effect is combined with race, it is magnified. Women also report negative mental health signs when all these demographic characteristic matches are happening at the same time. Additional tests suggest that reverse causality does not seem to be a major issue here.

Keywords: Demographic congruence, supervisor, subordinate, mental health

JEL: I12, J21, J24

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I. Introduction

The supervisor-subordinate similarities or differences have been found to affect workers' job attitudes or behaviors through the psychosocial notion of status consistency (Jackson 1962) or organizational views such as social identity theory (Tajfel & Turner, 1986) and similarity attraction paradigm (Byrne,1971). More specifically, if the supervisors' characteristics relative to those of subordinates comply with a set of social norms, the workers' emotional status or work behavior might change as well (Vancouver and Schmitt 1991; Vecchio 1993). As a social norm, for instance, a supervisor is usually expected to be older, more experienced and more educated than the subordinates (Perry et al 1999) and the failure to be so might result in negative impacts on the employees' outcomes (Mangione and Quinn 1975).

A significant body of literature has tested the association of the supervisor-subordinate congruence with job satisfaction, or the on-the-job utility measure that has been found to correlate with higher employee productivity together with fewer quits and a lower ratio of absenteeism (Mangione and Quinn, 1975; Freeman, 1978; Clegg, 1983). Other outcomes of interest that have been studied are job attitudes (Riordan & Wayne, 2008; Tsui, Egan, & O'Reilly, 1992; Wharton, Rotolo, and Bird, 2000; Williams and Meân, 2004) and commitment to jobs (Williams and O'Reilly, 1998) or physical health (Hoppe, Fujishiro and Heaney 2014).

Although there are numerous studies that examine the role of supervisors' behavior in determining employees' mental health (Martin and Schinke, 1998; Armstrong, Drew, and Henly,1984; Gavin and Kelley, 1978), there does not appear to be any work on the relationship between the demographic characteristics of the supervisors relative to those of the employees and clinical mental health. In this study, I use a national U.S. survey data to test the relationship between supervisors and subordinates' age, gender and race congruence and worker mental health,

and find that these characteristics could positively or negatively affect employees' mental health variables. More specifically, evidence suggests that men seem to show positive mental health signs when they have bosses of the same race and gender. They also seem to like supervisors who are almost the same age. On the contrary, women's mental health seem to be negatively affected when they have female supervisors. When the gender effect is combined with race, it is becomes even larger. They also report negative mental health signs when all these demographic characteristics are the same simultaneously. Furthermore, racial congruence seems to be associated with better mental health for Blacks and Non-Blacks (Non-Hispanics). For Hispanics, the effect is opposite, but statistically insignificant. Additional tests suggest that results do not seem to be driven by workers self-selection into particular jobs.

II. Background and Hypotheses

There are two main strands of research on the impact of supervisor on the subordinate outcomes. First, supervisors' performance can affect workers' job satisfaction. Artz et al. (2016) present some British and American longitudinal evidence that the technical competence of bosses can bring about more quality to the lives of their employees. Their paper is among the few recent studies that are interested in the direct causal relationship between supervisor quality and employee wellbeing. Previously, Branch, Hanushek and Rivkin (2013) and Lazear, Shaw and Stanton (2012) examined the impact of supervisors on employee productivity which is believed to affect wellbeing indirectly. Furthermore, constructive feedback from bosses (Sommer and Kulkarni, 2012), and boss supportiveness (Hassan and Chandarin, 2005; Hsu, 2011) are shown to improve job satisfaction.

Second, demographic characteristics of the boss are found to affect job satisfaction and other measures of the employee wellbeing. For instance, recent evidence such as that by Artz and

Taengnoi (2016) suggests that having female bosses might be negatively associated with female worker job satisfaction. In a different study, lower supervisor age is shown to be positively correlated with reduced job satisfaction specifically among more educated workers (Artz, 2013). However, of more interest for the purpose of the current study is the supervisor-subordinate congruence rather than the boss characteristics themselves. According to the literature, both the demographic (actual) supervisor-subordinate similarity and perceived similarity can affect employee outcomes such as their perception of relationship with the supervisor, although that perception might change through time (Turban, Dougherty and Jones 1988). In a different study, Campione (2014) examines the effect of differences in age, gender and race of the supervisor and subordinate on the employees' job satisfaction and by cross sectional evidence demonstrates that supervisors' relational demographic differences have a statistically significant negative impact on the employees' job satisfaction.

Although there is ample evidence that different aspects of work affect employees' mental and physical health (WHO 2000), empirical work on the relationship between supervisor and employee clinical mental health is rather scarce and is mostly conducted on boss behavior and performance. Earliest studies such as that of Gavin and Kelley (1978) find that employees' self-reported well-being are positively correlated with how considerate they believe their supervisors are. Sheridan and Vredenburgh (1978) also show that there is an inverse relationship between the supervisors' consideration and tension at work for the employees. Seltzer and Numerof (1988) examine the role of leader behavior in the prediction of job–related burnout and find that consideration and initiation of structure by leaders are important factors. Martin and Schinke (1998) find that harsh criticism by supervisors is positively associated with burnout. Tepper (2000) finds some evidence that abusive supervision is correlated with psychological distress. Nyberg

(2009), however, conducts a more comprehensive study and finds that attentive managerial leadership is significantly related to self-reported stress, age-adjusted self-rated health and sickness absence. In addition, she finds that self-centered leadership is related to poor mental health, vitality and behavioral stress.

According to Johnson & Hall (1988), De Lange et al. (2003) and O'Driscoll & Brough (2010), main workplace factors that might influence psychological well-being are demands, support and control. Boss demographics are affecting at least one of these factors. For example, a male boss might seem more or less controlling or supportive to the workers of the opposite sex. Also, people might receive more support from their supervisors of the same ethnicity of their own. Same logic applies to small age gaps between the supervisors and subordinates. In addition, Gilbreath (2006) believes supervisors can act as the source of stress if they mismanage, are disorganized or do not show interest in their employees as human beings. They can also be the moderator of stress and help employees deal with stressful situations or amplify the upsetting events. Either as the source of stress or the moderator of it, demographic characteristics seem to play a role for supervisors.

The relational demographic characteristics' impact on the employees' mental health studied in this paper is a new addition to the literature. It will allow us to examine how gender, age and ethnicity similarities between bosses and employees can affect employees' various mental health measures. The use of panel data in this study can also allow us to more specifically test this causal relationship both by following same individuals through time and restricting the sample solely to the workers who remain in the same workplace and only experience a change in the relational demographic characteristics of their supervisors.

III. Data and Methodology

There is only one significant source of data that includes the supervisor demographic characteristics (age, gender and race) and worker mental health information for multiple years. The National Longitudinal Survey of Youth (NLSY97) is a longitudinal panel survey of the US individuals born between 1980 and 1984. Since the mental health information is only available from 2000 and every other year afterwards, data from only even years from 2000 to 2010 are included in the sample.

This study revolves around employee self-reported mental health, and how it is associated with their demographic characteristics relative to those of their supervisors. Therefore, it will only be meaningful if employed individuals that have an employer (and a supervisor) remain in the sample. Subsequently, all military personnel and self-employed respondents are removed from the final sample which consists of 29,484 person years.

The dependent variable used in this study is the employees' mental health shown in different ways. The NLSY respondents answer several questions aimed at measuring their depression and overall mood. Questions have the following format: "How much of the time during the last month have you been a happy person?", "How much of the time during the last month have you felt calm and peaceful?", "How much of the time during the last month have you felt so down in the dumps that nothing could cheer you up?", " How much of the time during the last month have you been a very nervous person?", and "How much of the time during the last month have you felt downhearted and blue?".

The resulting dependent variable is categorical and gets the values 1 (1 All of the time), 2 (Most of the time), 3 (Some of the time), and 4 (None of the time).

The vector of control variables includes demographic characteristics such as race, age, and education, student status as well as job characteristics like annual earnings, tenure with employer, , and industry / occupation group. All variable descriptive statistics are presented in Table 3.1.

Table 3.1: Worker Descriptive Statistics (NLSY97)

Variables and definitions	Mean	St. Dev.
Male: = 1 if male and 0 if female	0.495	0.499
Hispanic: = 1 if Hispanic and 0 otherwise	0.214	0.410
Black: = 1 if Black and 0 otherwise	0.235	0.424
Age: age in years	23.411	3.556
Married: = 1 if married and 0 otherwise	0.193	0.395
Enrolled:= 1 if enrolled in a post-secondary program and 0 otherwise	0.289	0.453
Log annual earnings	8.208	3.376
Employer tenure in weeks	48.917	27.003
Reported being down in the past month: 1 all the time, 2 most of the time, 3 sometimes, 4 none of the time	3.232	0.662
Reported being depressed in the past month: 1 all the time, 2 most of the time, 3 sometimes, 4 none of the time	3.654	0.586
Reported being nervous in the past month: 1 all the time, 2 most of the time, 3 sometimes, 4 none of the time	3.254	0.677
Reported being happy in the past month: 1 all the time, 2 most of the time, 3 sometimes, 4 none of the time	2.195	0.649
Reported being peaceful in the past month: 1 all the time, 2 most of the time, 3 sometimes, 4 none of the time	2.376	0.677
Observations (person-years)	29484	

Supervisors' demographic characteristics studied are age, gender and race. However, what we actually require for the purpose of this paper, is whether supervisors and subordinates show congruence in these demographic characteristics. Thus the main independent variable is a dummy that is set to one if a worker's demographic characteristic is the same as her supervisor's and zero otherwise. The supervisors' descriptive statistics are shown in Table 3.2.

Table 3.2: Supervisor Descriptive Statistics

Variables and definitions	Mean	St. Dev.
Percentage of supervisors Black	0.130	0.345
Percentage of supervisors Hispanic	0.067	0.250
Supervisor male	0.461	0.498
Supervisor Age	38.504	12.718
Percentage of supervisors having the same gender as their subordinates	0.638	0.480
Percentage of supervisors being almost the same age as their subordinates	0.097	0.296
Percentage of supervisors having the same race as their subordinates	0.641	0.479

Since I examine mental health using non-linear ordered categorical variables, ordered probit or logit are the most common estimators. The baseline model specification to be estimated is shown in the equation below.

(1) $$MH_{it}^{*} = \propto + \beta_1' X_{it} + \beta_2 SupMatch_{it} + \varepsilon_{it}$$

Here MH_{it}^{*} is an unobservable dependent variable, which evaluates the state of the mental health of the individual i at time t. Its realization, MH_{it}, is a 4-category mental health variable that is observed as follows:

(2) $$MH_{it} = \begin{cases} 1 & MH_{it} < \mu_1 \\ 2 & \mu_1 < MH_{it} < \mu_2 \\ 3 & \mu_2 < MH_{it} < \mu_3 \\ 4 & \mu_3 < MH_{it} < \mu_4 \end{cases}$$

ε_{it} is an error term, which we assume follows standard normal distribution, $\varepsilon_{it} \in N(0,1)$, $SupMatch_i$ is an indicator that equals one if a worker has the same gender, race and (approximately) same age of the supervisor, and X is a vector of control variables mostly listed in Table 3.1. The coefficient of interest is β_2, reflecting the associations between supervisor-subordinate demographic congruence and employees' mental health.

It is also certainly plausible that the congruence in supervisor and subordinate demographic characteristics might happen concurrently. Thus, a new model specification includes interactions of different demographic matches between supervisors and subordinates.

(3) $MH_{it}^{*} = \propto + \beta_1' X_{it} + \beta_2 Sup\ ageMatch_{it} + \beta_3 Sup\ ageMatch_{it} \times Sup\ genMatch_{it} + \beta_4 Sup\ ageMatch_{it} \times Sup\ raceMatch_{it} + \beta_5 Sup\ raceMatch_{it} \times Sup\ genMatch_{it} + \beta_6 Sup\ raceMatch_{it} \times Sup\ genMatch_{it} \times Sup\ ageMatch_{it} + \varepsilon_{it}$

The definition of the dependent variable and the vector of controls will be the same. The purpose of the interaction terms is to examine whether one demographic characteristic match variable significantly affects how another demographic characteristic variable impacts subordinates' mental health. For instance, β_5 indicates whether the race match with supervisor is associated with employee mental health differently between workers whose bosses have the same gender or vice versa. This model also acts as a robustness check for the previous model.

IV. Results

Table 3.3 reports the supervisor-subordinate age congruence estimation results from an ordered probit specification in a panel setting. Column (1) represents the estimations without the inclusion of any covariates. Column (2) offers the same estimates after the inclusion of demographic covariates and column (3) adds the job characteristics. In this simple specification, it is shown having a boss who is no more than 5 years different in age from her employees can make them less nervous, depressed or down while increasing the chances of being happy and peaceful. However, other than the coefficient of feeling down for males, all the other coefficients are not statistically significant, although they are all nearly identical to each other. As it can be seen, adding demographic controls and job characteristics does not change this overall trend.

Table 3.3: Baseline Estimations (Random Effects Ordered Probit- Age Congruence)

A. Mental Health Variables (Males)	**(1)**	**(2)**	**(3)**
Nervous	-0.029	-0.002	-0.003
	(1.06)	(0.06)	(0.08)
Down/Blue	-0.104	-0.065	- 0.059
	(2.78)***	(1.53)	(1.39)
Depressed	-0.007	0.026	0.023
	(0.17)	(0.53)	(0.48)
Happy	0.002	0.006	0.001
	(0.07)	(0.16)	(0.03)
Peaceful	0.044	0.032	0.028
	(1.24)	(1.31)	(0.68)
Demographic Controls	No	Yes	Yes
Job Dummies*	No	No	Yes
B. Mental Health Variables (Females)			
Nervous	0.033	- 0.038	-0.041
	(0.86)	(0.85)	(0.92)
Down/Blue	0.008	-0.011	-0.011
	(0.22)	(0.27)	(0.26)
Depressed	-0.033	-0.016	-0.015
	(0.79)	(0.33)	(0.32)
Happy	0.029	0.019	0.018
	(0.77)	(0.45)	(0.41)
Peaceful	0.001	0.023	0.042
	(0.03)	(0.67)	(0.97)
Demographic Controls	No	Yes	Yes
Job Dummies*	No	No	Yes

Notes: The reported are coefficients from ordered probit specifications and each row is from a separate regression for each mental health variable. T-statistics are in parentheses and are calculated after bootstrapping the standard errors for the individuals.
*** Significant at the 1 percent level
** Significant at the 5 percent level
* Significant at the 10 percent level

Table 3.4 presents the results of equation (1) estimations for gender congruence. Interestingly, results show that there seem to be different impacts of supervisor-subordinate gender congruence on men and women's mental health. More specifically, while men indicate negative correlations for the unfavorable mental health variables (being nervous, down or depressed), women show positive associations. In other words, women seem to be negatively affected by their female supervisors. The estimates are statistically significant and consistent for all mental health variables. Furthermore, women with female bosses provide some evidence of less happiness and peace of mind. This is the opposite case for men with negative associations for the latter variable.

Table 3.4: Baseline Estimations (Ordered Probit- Gender Congruence)

A. Mental Health Variables (Males)	**(1)**	**(2)**	**(3)**
Nervous	-0.124	-0.060	-0.058
	(5.29)***	(2.06)**	(2.01)**
Down/Blue	-0.092	-0.024	-0.021
	(4.02)***	(2.44)**	(2.08)**
Depressed	-0.080	-0.016	-0.012
	(3.01)***	(3.09)***	(2.37)**
Happy	0.006	0.004	0.003
	(0.75)	(0.60)	(0.44)
Peaceful	0.022	0.016	0.026
	(1.02)	(0.63)	(0.98)
Demographic Controls	No	Yes	Yes
Job Dummies*	No	No	Yes

B. Mental Health Variables (Females)			
Nervous	0.110	0.040	0.037
	(4.59)***	(1.45)	(1.29)
Down/Blue	0.162	0.054	0.041
	(6.88)***	(1.98)**	(1.49)
Depressed	0.119	0.026	0.024
	(4.45)***	(5.23)***	(4.84)***
Happy	-0.007	-0.006	-0.033
	(0.33)	(0.22)	(0.12)
Peaceful	-0.064	-0.034	-0.026
	(2.76)***	(1.25)	(0.95)
Demographic Controls	No	Yes	Yes
Job Dummies*	No	No	Yes

Notes: The reported are coefficients from ordered probit specifications and each row is from a separate regression for each mental health variable. T-statistics are in parentheses and are calculated after bootstrapping the standard errors for the individuals.
*** Significant at the 1 percent level
** Significant at the 5 percent level
* Significant at the 10 percent level

Table 3.5 provides some evidence on the effect of race match between the supervisors and employees on the employees' metal health. Overall, the estimates (that are not statistically significant in many cases) suggest that having a boss from one's own race can have minor positive consequences in terms of mental health. Results are broadly the same for men and women and do not considerably change once I control for demographic and job characteristics.

Table 3.5: Baseline Estimations (Ordered Probit - Race Congruence)

A. Mental Health Variables (Males)	**(1)**	**(2)**	**(3)**
Nervous	-0.078	-0.068	-0.061
	(2.79)***	(2.03)**	(1.80)*
Down/Blue	-0.025	-0.019	-0.012
	(0.96)*	(0.62)	(0.38)
Depressed	0.022	0.012	0.016
	(0.72)	(0.10)	(0.44)
Happy	0.025	0.019	0.013
	(0.99)	(0.63)	(0.44)
Peaceful	0.068	0.012	0.010
	(2.65)*	(1.71)*	(1.11)
Demographic Controls	No	Yes	Yes
Job Dummies*	No	No	Yes
B. Mental Health Variables (Females)			
Nervous	-0.115	-0.113	-0.111
	(4.31)***	(2.61)**	(1.15)
Down/Blue	-0.024	-0.006	0.001
	(0.95)	(0.21)	(0.14)
Depressed	0.049	0.004	0.002
	(1.71)*	(0.08)	(0.06)
Happy	-0.020	-0.022	-0.013
	(0.77)	(0.57)	(0.22)
Peaceful	0.041	0.018	0.017
	(1.70)*	(1.67)*	(0.99)
Demographic Controls	No	Yes	Yes
Job Dummies*	No	No	Yes

Notes: The reported are coefficients from ordered probit specifications and each row is from a separate regression for each mental health variable. T-statistics are in parentheses and are calculated after bootstrapping the standard errors for the individuals.
*** Significant at the 1 percent level
** Significant at the 5 percent level
* Significant at the 10 percent level

Although the race congruence coefficients are mostly insignificant, it would be interesting to see if same is true across all races. Thus, same model estimates are also presented after stratifying the sample by race. Table 3.6 consists of the ordered probit model results and as shown, interestingly Black workers' better mental health seem to be positively correlated with having a Black boss. Same can be said about non-Blacks and Non-Hispanics. The opposite is true for Hispanics, although the estimates are statistically insignificant.

Table 3.6: Ordered Probit Models – (Race Congruence Stratified by Race)

A. Mental Health Variables (Across Different Races)	**(Nervous)**	**(Down)**	**(Depressed)**	**(Happy)**	**(Peaceful)**
Black	- 0.037	- 0.001	-0.102	0.136	0.168
	(1.01)	(0.04)	(2.29)**	(2.21)**	(1.25)
Hispanic	- 0.021	0.002	0.062	-0.028	-0.0001
	(0.54)	(0.05)	(1.33)	(0.69)	(0.00)
Mixed race (Non-Hispanic)	-0.126	0.168	0.012	-0.439	-0.107
	(0.34)	(0.43)	(0.36)	(1.31)	(0.30)
Non-Black (Non-Hispanic)	- 0.069	-0.009	-0.048	0.051	0.077
	(2.23)**	(0.28)	(1.26)	(1.54)	(2.32)**

Notes: The reported are coefficients from ordered probit specifications and each row is from a separate regression for each mental health variable. T-statistics are in parentheses and are calculated after bootstrapping the standard errors for the individuals.
*** Significant at the 1 percent level
** Significant at the 5 percent level
* Significant at the 10 percent level

It is also critical to recognize that different demographic characteristics of the boss can have concurrent effects on the employee's mental health. For instance, a female employee might be unhappy with a supervisor who is both female and relatively young. Thus, Table 3.7 provides estimates of an ordered probit model in which I also add interaction terms of age, gender and race, two by two and all three together. Results indicate that the combination of a supervisor being of the same race and gender makes men less nervous and happier with statistically significant estimates. In addition, men seem to like the combination of similar age and gender of the supervisors. Same can be said about all the demographic characteristics happening together.

Women, on the other hand, have a different story. Similar to the previous results, they seem not to like the gender match with their supervisors. When gender is combined with race match the effect is even more significant. Women also seem not to like the combination of age, gender and race match altogether, as the coefficients on this interaction term communicate this information.

Table 3.7: Ordered Probit Models with Interactions

A. Mental Health Variables (Males)/Covariates	**(Nervous)**	**(Down)**	**(Depressed)**	**(Happy)**	**(Peaceful)**
Age	-0.003	- 0.143	- 0.021	-0.068	- 0.168
	(0.04)	(1.58)	(0.20)	(0.78)	(1.94)*
Gender	- 0.011	- 0.081	- 0.060	0.029	0.067
	(0.25)	(1.81)*	(1.15)	(3.08)***	(1.57)
Race	-0.012	0.001	- 0.018	-0.028	0.012
	(0.28)	(0.03)	(0.36)	(0.69)	(0.29)
Race*Age	-0.009	-0.136	0.039	0.156	0.212
	(0.07)	(0.98)	(0.24)	(1.15)	(1.58)
Race*Gender	-0.124	0.001	0.012	0.056	0.102

	(2.14)**	(0.02)	(0.19)	(1.04)	(1.92)*
Age*Gender	-0.081	0.145	0.041	0.243	0.288
	(0.60)	(1.11)	(0.27)	(2.14)**	(2.33)**
Age*Race*Gender	0.100	0.152	0.013	0.416	0.383
	(0.54)	(0.85)	(0.07)	(2.39)**	(2.22)**
B. Mental Health Variables (Females)/Covariates					
Age	0.180	0.021	-0.015	-0.019	-0.098
	(1.38)	(0.17)	(0.11)	(1.17)	(0.79)
Gender	0.088	0.156	0.143	-0.070	-0.013
	(1.79)*	(3.29)***	(2.70)***	(1.48)	(0.28)
Race	-0.100	0.028	0.117	0.004	0.101
	(1.90)*	(0.56)	(2.08)***	(0.10)	(1.99)**
Race*Age	-0.222	0.117	0.115	0.183	0.216
	(1.37)	(0.75)	(0.66)	(1.16)	(1.39)
Race*Gender	0.008	-0.038	-0.075	-0.078	-0.082
	(0.14)	(0.67)	(1.15)	(1.35)	(3.04)***
Age*Gender	-0.142	-0.099	0.067	-0.043	0.119
	(0.92)	(0.67)	(0.41)	(0.29)	(0.81)
Age*Race*Gender	0.002	-0.149	-0.366	0.148	-0.159
	(0.01)	(0.79)	(1.72)*	(0.78)	(2.47)**

Notes: The reported are coefficients from ordered probit specifications and each column is from a separate regression for each mental health variable. T-statistics are in parentheses and are calculated after bootstrapping the standard errors for the individuals.
*** Significant at the 1 percent level
** Significant at the 5 percent level
* Significant at the 10 percent level

Yet another concern is that unobserved characteristics that are correlated with worker mental health are also correlated with the choice to work under supervision of supervisors with different demographic characteristics. This implies that it is not the relative demographics of the supervisors

that is associated with variations of employee mental health, but instead it is the sorting of particular workers into positions with particular supervisors.

To take account of this issue, first the models are all estimated using a random effects strategy and second providing a comparison of the results between samples of people who always remained in the same job (but their supervisors' relative demographic characteristics changed) and those who moved between jobs. This, indeed, does not definitively solve the sorting problem, it does, however, offer a simple comparison of the difference between the workers who remained in the same job for multiple years and those who sorted themselves into a different job.

The comparison is made using the estimates in Table 3.8. If sorting is any statistically significant explanation for the previously presented results, then there should be a statistically significant difference between the estimates in these two groups. The results, however indicate that men still like or at least do not mind gender and race similarity to their supervisors whereas women significantly show signs of worse mental health as a result of gender match with their supervisors. Since, the results do not meaningfully change, worker sorting is unlikely to be the main reason for these results.

Table 3.8: Ordered Probit Models with Sub-sample Estimations (Never changed jobs)

A. Mental Health Variables (Males)	**(Age)**	**(Gender)**	**(Race)**
Nervous	-0.098	-0.093	-0.249
	(0.77)	(1.08)	(2.71)***
Down/Blue	-0.039	-0.024	-0.084
	(1.70)*	(3.21)**	(1.13)
Depressed	0.040	-0.151	-0.178
	(0.27)	(1.94)*	(1.70)*
Happy	0.006	0.013	0.041
	(0.91)	(2.20)*	(0.57)

Peaceful	0.014	0.090	0.117
	(0.13)	(1.41)	(1.63)
Demographic Controls	Yes	Yes	Yes
Job Dummies*	Yes	Yes	Yes
B. Mental Health Variables (Females)			
Nervous	0.232	0.231	-0.152
	(1.79)*	(2.59)***	(1.77)*
Down/Blue	0.106	0.206	-0.069
	(0.71)	(1.96)**	(0.80)
Depressed	-0.075	0.227	-0.110
	(0.47)	(1.94)*	(1.00)
Happy	0.295	-0.031	0.027
	(2.05)**	(0.36)	(0.33)
Peaceful	0.142	-0.009	0.097
	(2.11)**	(0.12)	(1.12)
Demographic Controls	Yes	Yes	Yes
Job Dummies*	Yes	Yes	Yes

Notes: The reported are coefficients from prdered probit specifications and each row is from a separate regression for each mental health variable. T-statistics are in parentheses and are calculated after bootstrapping the standard errors for the individuals.
*** Significant at the 1 percent level
** Significant at the 5 percent level
* Significant at the 10 percent level

V. Conclusion

A supervisor's characteristics can affect worker's various outcomes and behaviors such as job satisfaction, performance or mental health. This study is the first of its kind to provide some evidence that a supervisor's age, gender and race match with those of an employee correlates with either better or worse worker mental health. The results remain broadly the same after controlling

for demographic and job characteristics. Moreover, the relative demographic measures retain their general pattern after including interaction terms and restricting the sample to the employees who remained in the sample and never changed jobs all through.

Thus, the study's major contribution to the literature is that not only do the supervisor's competence and performance affect employees' mental health, but the demographic characteristics relative to their employees' can also play such a role. It particularly shows that men's mental health does not seem to be negatively affected by the race, gender or age congruence. In fact, in the case of gender and race congruence, their mental health seems in a better status. Women's mental health is worsened under supervision of women. The effect is even more noticeable when age and race also match with the supervisors. Finally, racial congruence between supervisors and employees seems to be a positive phenomenon for Blacks and Non-blacks (Non-Hispanics) whereas the opposite is true for Hispanics and mixed races.

One limitation of this study is the unavailability of more mental health variables that would enable the author to construct one single mental health index. One benefit of doing so would be the ease of estimating various linear models, whereas in the current paper we are limited to maximum likelihood estimation methods. This would have also allowed for the control of fixed effects, and through it taking account of selection bias in a more plausible way. But data on boss demographic characteristics together with mental health variables are only found in the NLSY97, and there is no other datasets to the author's knowledge. In addition, for better taking care of selection bias in the study, other methods of data collection such as natural experiments seem a good candidate. Regardless of the methodology limitations, this study provides brand new evidence on a channel that supervisors might affect their employees' health. Any organization's

human resource department that values employee's mental health and its proven impact on their performance might want to consider this fact before assigning employees to different sections.

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Williams, K. Y., & O’Reilly III, C. A. (1998). A Review of 40 Years of Research in Organizational Behavior, 20, 77-140.

Curriculum Vitae

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FIELDS

Health Economics, Labor Economics, Other Applied Microeconomics (Transportation and Online Consumer Behavior)

FUTURE POSITION

RTA Professor of Economics, James Madison University, Harrisonburg, Virginia

OTHER TEACHING INTERESTS

Micro/Macroeconomics, International Finance and Trade, Money and Banking, Business Economics (Financial Markets and Institutions, Principles of Finance, Intermediate Finance and Managerial Economics)

EDUCATION

Ph.D. in Economics, University of Wisconsin-Milwaukee **August 2016**
Dissertation: "Essays on Health and Labor Market Practices in the U.S."
Advising Committee: Scott Drewianka, Scott Adams, John Heywood, Owen Thompson

M.A. in Economics and Electronic Business, University of Tehran, Iran **2009**
Thesis: "A Survey on Effective Factors in Selection of an Internet Brand in Iran"

B.A. in Economics, University of Tehran, Iran **2006**

Certificate in Advanced English (CAE), University of Cambridge **2005**

RESEARCH PAPERS

"The Relationship between Nonstandard Work Schedules and Substance Use. New Evidence from the NLSY97" (**Under Review)**

"The Effect of Alcohol Consumption on Job Search Behavior: A Regression Discontinuity Application of Minimum Drinking Age Laws"(**Under Submission)**

"Evaluating Efficiency of Passenger Railway Stations: A DEA Approach," **Revise and Resubmit to Research in Transportation Business & Management.** (With Melody Khadem Sameni and John M. Preston)

"The Impacts of Doubling Tracks and Electrifying Lines On Capacity Utilization: A Worldwide Panel Study," **Revise and Resubmit to the Journal of Rail Transport Planning and Management**. (With Melody Khadem Sameni and John M. Preston)
"The Supervisor-Subordinate Demographic Congruence and Employees' Mental Health"

"Evaluation of Internet Purchase Intention Models (Case Study: Internet Book Purchase in Iran)," Proceedings of the IADIS International Conference on e-Society, Porto, Portugal: IADIS Publications, 2010. (With Bahman Ajdari and Siamak Rafati Khosroshahi)

CURRENT PROJECTS

"The Effect of Health Information Technology on the Quality of Primary Care"

"The Effect of Prescription Drug Monitoring Programs on Drug-Related Mortalities"

TEACHING EXPERIENCE

Instructor, Dept. of Economics, UW-Milwaukee **2011-2016**

- Principles of Microeconomics (2 sections)
- International Economic Relations (Economics senior level) (2 sections)
- Principles of Macroeconomics (6 sections)

Lecturer, Cardinal Stritch University, College of Business and Management 2014-2015

Microeconomics (Blended format)

Lecturer, Sheldon B. Lubar School of Business, UW- Milwaukee **2015**

Financial Institutions (Finance senior level) (2 sections)

Teaching Assistant, UW- Milwaukee, Dept. of Economics **2011- 2015**

- Economics of Employment Relations (Graduate/undergraduate)
- Principles of Microeconomics (4 sections)
- Principles of Macroeconomics (6 sections, 2 online)

Teacher, Iran Language Institute (Formerly Iran America Society) **2004-2008**

English Language (Various levels, part-time)

TEACHING ENHANCEMENT

Course Development, Healthcare Economics, Cardinal Stritch University, January 2015
Faculty Training Course, Cardinal Stritch University, November 2014

HONORS AND AWARDS

Richard Perlman Prize for Outstanding Paper in Labor Economics, UWM, 2015
Research Presentation Honorarium, UWM Dept. of Economics, 2015
Graduate Travel Award (2), UWM, 2015
Graduate Assistantship and Tuition Remission Award, UWM, 2011-2014 & 2015
University of Tehran Undergraduate and Graduate Fellowship, 2002-2009

PRESENTATIONS/ DISCUSSIONS

Midwest Economic Association Annual Meeting, 2016 (Upcoming)
UWM Applied Microeconomics Workshop, UWM Dept. of Economics, 2016 (Upcoming)
American Public Health Association Annual Meeting, 2015
Southern Economic Association Annual Meeting, 2015
Midwest Economic Association Annual Meeting (SOLE session), 2015
Seminar and Applied Microeconomics Workshop, UWM Dept. of Economics, 2014 & 2015
Wisconsin Economic Association Annual Meeting, 2014
IADIS International Conference on e-Society, Porto, Portugal, 2010

OTHER PROFESSIONAL EXPERIENCE

International Division, Bank Mellat Headquarters, Tehran, Iran **2007 - 2010**

- International Finance and Banking Analyst
- E-banking adviser to the general manager
- Research Associate for the feasibility study of Bank Mellat's subsidiary in Malaysia

Pedagogical Researcher, Iran Language Institute **2005**

"The Evaluation of Motivation and Motivating in English as a Foreign Language Classes"

Project Assistant, University of Tehran **2003**

"The Effect of Petrochemical Industry on Iran's Environmental Value Added," (With Shirin Sabetghadam)

PROFESSIONAL ASSOCIATIONS

- American Economic Association
- American Public Health Association
- Midwest Economic Association
- Southern Economic Association

SERVICE

- **Panelist,** University-wide New Teaching Assistants Orientation, University of Wisconsin Milwaukee, 2012, 2014 & 2015
- **Economics Booth Coordinator,** UWM Open House, 2011 and 2012
- **Team Captain,** UWM Dept. of Economics Holidays Contest for Graduate Students, 2013

COMPUTER SKILLS

- Proficient in : Stata, Maple, EViews , Microsoft Office
- Familiar With : SAS, SPSS, Latex, HTML coding

LANGUAGE SKILLS

English (Fluent), Persian (Native), Spanish (Functional)

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