A Statistical Analysis of Some Aspects of Well-Being of South Korean Elderly Population.

by

Tae-Young Pak

(Under the direction of Abhyuday Mandal)

Abstract

This thesis considers the determinants of well-being among the elderly population of South Korea. Two essays examine whether and to what extent institutional change or individual choice affects the subjective and objective aspect of well-being. In the first essay, we examine how an institutional change in South Korea, through the increase in basic pension benefits, influences life satisfaction. The subjective well-being outcome has been the subject of intense exploration in epidemiology and gerontology literature due to its health implications. The previous studies have shown that poor life satisfaction is a major determinant of mental illness and leads to progressive decline in cognitive and physical functioning. Despite the importance of subjective well-being in the elderly population, the impact of non-individual socioeconomic factors is not well understood. This essay contributes to the literature by examining whether the expansion of pension benefits in South Korea increased happiness among beneficiaries. The second essay concerns the correlations between smoking and cognitive functioning. Among many domains of physical health, cognitive functioning has drawn renewed interest as a precursor of dementia and Alzheimer's disease at later life. The recent studies have shown that smoking may have a protective effect on cognitive functioning through the delivery of nicotine to the brain. In this essay, we link the smoking behaviors of husbands to the wife's cognitive functioning to evaluate the cognitive effects of secondhand smoke exposure.

INDEX WORDS: Non-contributory pension, Subjective well-being, Financial satisfaction, Old-age poverty, Cognitive functioning, Secondhand smoke exposure

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Chapter 1

Introduction

The first essay, entitled "The effects of non-contributory pensions on subjective well-being: Evidence from the Basic Pension in South Korea", evaluates the impact of the 2014 expansion of the Basic Pension program on subjective well-being using novel empirical strategy. The basic old-age pension aims to provide basic income support to the Korean elderly who lack fixed income stream. Beginning in 2014, the level of monthly benefit is doubled to tackle a growing elderly poverty in South Korea. This study exploits the 2014 reform as a natural experiment to examine the subjective well-being effect of basic pension. We used data from the Korean Longitudinal Study of Aging and a propensity score matched difference-in-differences approach to account for bias on observables and unobserved individual heterogeneity. The results show that financial satisfaction increased by 4.8-5.7% among pension beneficiaries relative to the pre-treatment level. However, there is no evidence of indirect impact that extends to improvements in health satisfaction, relationship satisfaction, and overall quality of life. Our findings imply that the reform has been successful in reducing elderly poverty but done little to improve quality of life.

The second essay, entitled "Secondhand smoke exposure and cognitive performance in South Korean elderly population", examines the impact of secondhand smoke exposure on the partner's cognitive functioning among married couples. The research questions are evaluated by analyzying the longitudinal data for a national sample of Korean elderly. Empirical models are estimated by a fixed effects model to account for the individual-specific time constant factors that may influence both smoking behavior and cognition. Our findings indicate that non-smoking spouses whose partner is currently smoking perform better than those who live with former smokers on cognition tests. The estimated cognition-enhancing effect of secondhand smoke exposure ranges from 1.4% to 1.7%. Results from robustness tests showed a limited influence of family-level characteristics such as household income and total net worth and a potential feedback effect in which smoking cessation could be driven by the mortality outcomes of non-smoking spouses. Additional analyses indicate that cognitive benefits of secondhand smoke will be negligible among demented subjects. Our findings, taken together with the previous evidence, suggest that secondhand smoke exposure may have a modest but positive influence on cognitive functioning.

Chapter 2

Essay I: The Effects of Non-Contributory Pensions on Subjective Well-Being: Evidence from the Basic Pension in South Korea

2.1 Introduction

Developing countries have experienced rapid growth in old age population. Unlike industrialized nations that have proceeded much slower with a demographic transition, developing countries entered aged society without having enough social protection (United Nations, 2013). The potentially serious economic and social consequence of population aging is old age poverty. To achieve financial sustainability in retirees, contributory pension schemes have been introduced and mandated to regular wage earners. However, this approach has proved to be difficult to provide required social safety nets in less developed economies with large informal labor sectors (Dethier et al., 2010; Galiani and Weinschelbaum, 2012). As a result, contributory pension programs have done little to protect seniors from vulnerability and deprivation (Pallares-Miralles et al., 2012).

A number of countries have responded to elderly poverty with social pensions. A social pension is a regular cash transfer to older people that aims to guarantee a minimum income (Salinas-Rodrguez et al., 2014). Eligibility is determined by age, citizenship/residency, and means-testing of income and wealth, but does not require a regular contribution. The social pension has been widely adopted in Africa, Latin America, and Southeast Asia to expand income security to households who are not covered by contributory pension programs (Robalino and Holzmann, 2009). The literature generally agrees with the poverty-reducing effect of non-contributory pensions (Bando et al., 2016; Deaton and Case, 1998), with some studies reporting secondary benefits to physical and mental health (Case, 2004; Galiani et al., 2016).

The elderly poverty rate in South Korea has been the highest among the OECD countries. Korean age-boomer generations have lived through a rapid economic growth without having prepared for their silver years. During their youth, a majority of these seniors have not held a regular job that requires them to contribute to the National Pension Service. In 2016, nearly half of the seniors above age 65 were living below the poverty line (Kim et al., 2016). To provide a stable income source, the South Korea government introduced the basic old-age pension (BOAP) in 2008. The BOAP is a non-contributory social welfare program that transfers flat-rate cash benefits to the elderly in need. This program has covered more than two-thirds of the elderly population but offered only small benefits that cover 16% of the minimum living expenses (Jones and Urasawa, 2014). Since July 2014, the benefit level was doubled to provide more realistic financial support. To date, the efficacy of the BOAP has yet to be fully understood.

The previous studies have examined the introduction of the BOAP in 2008 and found mixed evidence of poverty reduction (Kang and Choi, 2010; Lee and Kwon, 2016; Park and Kim, 2015; Shin and Do, 2015). One of the major weaknesses in these studies is the inclusion of the 2007-2008 financial crisis in the study period. If low-income households were more severely affected by the recession through early retirement, the policy effect could be offset by unobserved business cycle effect and underestimated in the empirical model. Moreover, the BOAP is accompanied by broader social welfare reform in 2008, which included the establishment of Korean long-term care insurance. Since disability is more pronounced for the economically disadvantaged group, it could also mask the income effect induced by the BOAP.

This study examines the impact of the BOAP on subjective well-being. We pay particular attention to the subjective aspect to capture the effect of pension income that extends to the overall quality of life. While poverty-related measures offer valuable information on material well-being, they do not show a full dynamic relationship between income security and life satisfaction. For empirical modeling, we exploit a unique natural experiment provided by the expansion of benefits in 2014. This approach has an empirical advantage over the previous studies as macroeconomic condition was relatively stable and no other major policy change occurred during this period. Using data from the Korean Longitudinal Study of Aging (KLoSA), the policy effect is estimated by comparing pre vs. post-expansion changes in subjective well-being scores between beneficiaries and non-beneficiaries. Since the BOAP is established as voluntary benefits, a difference-in-differences (DD) model is combined with propensity score matching (PSM). The combination of these two methods allows us to account for time-invariant unobservables that lead to self-selection into the program and compare only those with the most similar observable characteristics.

The subjective well-being is measured by financial satisfaction, health satisfaction, relationship satisfaction (parents-children), and general life satisfaction. We expect to estimate the direct impact of the reform from changes in financial satisfaction, and indirect spillover effect from other measures of well-being. For instance, as additional income increases access to healthcare or prescription drug adherence, subjective assessment of health status would have improved with the reform. Moreover, one might anticipate more intimate relationship between parents and children if the BOAP crowded out upstream financial transfers from children and eliminated potential within-family conflicts concerning informal support. Examining relationship satisfaction will shed lights on whether or not the BOAP is accompanied by a significant shift in traditional social norms on familial support for old age.

Our estimation results show that the 2014 expansion of the BOAP significantly improved financial satisfaction among beneficiaries. Through 2012 and 2014 the financial satisfaction score has decreased in the comparison group, whereas beneficiaries have reported nearly the same assessment of their financial situation. Compared to the pre-expansion level, the reform was responsible for approximately 5% increase in financial satisfaction. The correlations with other domains of well-being were statistically insignificant or significant but could not pass the parallel trend assumption. These results suggest that the BOAP achieved the policy objective to improve financial well-being among the elderly. No effects on other domains of subjective well-being are broadly consistent with the evidence that money does not buy happiness (Easterlin, 1995).

This study contributes to the existing literature along several dimensions. First, this study uses self-assessed satisfaction as the measures of subjective welfare. Most previous studies used mental health to proxy for the quality of life and failed to disentangle well-being effect from a health channel that mediates through increased healthcare. Second, our findings have implications for income effect on relative happiness. Respondents in the KLoSA were asked to rate their satisfaction level in comparison with people at similar ages. This allows us to examine whether or not universal income transfer that has limited influence on relative income affects happiness. Given that most of the evidence on the comparison income effect comes from country-level analysis, this study is a valuable addition to happiness studies. Third, we take advantage of a long panel and show that anticipatory effect is nearly non-existent in our results. Fourth, the sample is predominantly retirees at the mid-70s who have relatively homogeneous characteristics. Unlike previous studies that examined seniors at the 60s, our empirical models are less prone to omitted variable bias due to unobserved characteristics.

The rest of the paper is organized as follows. Section 2.2 introduces the background of the BOAP and reviews the literature on non-contributory pension programs in developing countries. Section 2.3 describes the data and empirical strategy to estimate matched DD models. Section 2.4 presents matching results and regression estimates, including covariate balancing test and matching score estimation. Section 2.5 concludes the paper with a discussion about limitations and future research.

2.2 Background

2.2.1 Basic Old-Age Pension in South Korea

The primary source of old-age income support in South Korea is the National Pension Scheme (NPS). The NPS is established through the National Pension Act of 1988 to extend pension coverage to the general public. This scheme is a partially-funded contributory pension that provides monthly income support at the full benefits age. Initially, the coverage was mandated on regular employees in workplaces with ten or more employees but gradually expanded to include small firms and the self-employed. Beginning in 1999, the NPS became a universal mandatory scheme for the public (see, Moon, 2009 for more details).

The NPS requires participants to contribute at least ten years to be eligible for benefits. Due to its late start, many of today's elderly population could not join the program or contributed only for minimum ten years. In addition, a unique structure of Korean labor market left many non-standard workers, such as contingent and part-time workers, out of the NPS (United Nations, 2016). In 2012, only 43% of the working-age population was contributing to the NPS, and 29% of the elderly population was receiving pensions from the NPS (Jones and Urasawa, 2014). The average pension benefit was $276 per month, which is far below the target replacement rate of 60% (Lee, 2017).

To provide supplemental income support and complement the NPS, the basic old-age pension (BOAP) scheme was introduced in January 2008. The BOAP is a means-tested non-contributory pension program for the elderly population whose income is lower than a threshold. To qualify for the BOAP, monthly household income plus income-equivalent wealth should be less than $600 for a single and $1,000 for a married couple in 2009 dollar. In the first year, the program covered seniors above age 70 at the bottom 60 percentile of income. Since January 2009, this eligibility rule is expanded to include those aged 65 and older who were below the 70% income scale. The monthly benefit was set at the 5% of the average monthly income of the NPS participants, which was equivalent to $84 for a single person household and \$139 for a married couple in 2008 dollar (Shin and Do, 2015). Although participation rate has been around 67% among age-eligible individuals (Lee and Wolf, 2014), the pension amount was small and covered only one-fifth of the poverty threshold (Moon, 2009).

Beginning in July 2014, the Basic Pension (BP) scheme replaced the BOAP and doubled the maximum monthly benefit to \$168 for singles and \$269 for married couples. This reform was in line with a new president Park's electoral promise to provide more realistic income support to seniors. Though the original promise was to expand coverage to all senior citizens, budgetary reasons led to keep the same asset-based eligibility rules (Lee et al., 2017). Under the BP scheme, monthly benefit is designed to decrease with benefits from the NPS and other public transfer programs. For instance, beneficiaries of the National Basic Livelihood Security (NBLS) who qualify for the BP receive less monthly benefits from the NBLS after deducting the BP benefit. Likewise, pension income from the NPS leads to proportionately smaller benefits from the BP. These changes are driven largely by political considerations to maintain wide coverage with limited social spending (Moon, 2009). Although this reform is a significant improvement in scope and depth in comparison to its predecessor, its impact on poverty reduction is unclear because basic pension benefits have not increased in the extreme poverty group.

There has been mixed evidence on the efficacy of the BOAP. The previous studies have linked several domains of financial well-being, including household income, consumption, and poverty, to the introduction of the BOAP in 2008. Among studies that employed quasi-experimental design, the impact of BOAP was found either statistically insignificant (Lee and Cho, 2015; Lee and Moon, 2014) or significant but not economically meaningful in terms of magnitude (Lee and Kwon, 2016; Park and Kim, 2015; Shin and Do, 2015). The only study on subjective well-being was Kang and Moon (2013). Much like other studies, they found small increase in financial satisfaction, which corresponds to a 2% increase relative to a pre-2008 level. As discussed above, the effect of the BOAP would have been much greater if there were no unobserved factors that have differential impacts on eligible and ineligible groups. A recent study by Lee et al. (2017) demonstrated that the expansion in 2014 resulted in a significant poverty reduction and consumption increase, while having little impact on private transfer.

2.2.2 Impact of Non-Contributory Pension on Economic Security and Well-Being

Most social pensions are designed as a non-contributory program that targets individuals who were not covered by pay-as-you-go contributory pensions (Dodlova et al., 2018). The traditional contributory structure has proved to be difficult to fully scale up in economies with large informal labor markets (Dethier et al., 2010; Galiani and Weinschelbaum, 2012). Compared to workers in the formal sector, individuals in small or family-based business have no access to an employer-provided pension or are not required to contribute to a national pension. In Africa, mandatory pension scheme coverage ranges from 1% to 35%, with only 1% of GDP being accrued to the pension system (World Bank, 2012). As a result, non-contributory pension is designed to be universal and grant eligibility based only on age and income (Holzmann and Jousten, 2013; McKinnon and Sigg, 2006). In general, social pension benefits are thinly but uniformly spread out over a large segment of the population (Salinas-Rodriguez et al., 2014).

Cash transfer through non-contributory pension has proved to be an efficient way to alleviate the depth of poverty as well as its incidence. Evidence from Brazil and South Africa found that households with a social pension recipient have a 12-18% lower probability of being poor than those not receiving benefits (Barrientos, 2003). Similarly, non-contributory pension in Argentina led to a significant poverty reduction, with effects more pronounced for extreme poverty (Bertranou and Grushka, 2002). Households with pension beneficiaries have greater financial stability and are less likely to experience poverty in subsequent periods (Barrientos and Lloyd-Sherlock, 2002). Policy simulation in sub-Saharan African countries showed that universal non-contributory pensions would reduce indigence headcount and gap when employed (Kakwani and Subbarao, 2007).

The social pension has shown to have spillover effects on well-being and health. In a study of South Africa's state old age pension, beneficiaries exhibit less depressive symptoms and improvements in self-reported health after receiving transfers (Case, 2004). The subsequent studies in Mexico and Peru found similar evidence of material well-being and mental health benefits among beneficiaries (Bando et al., 2016; Galiani et al., 2016). In a recent study of the Rural Pension Scheme in China, Cheng et al. (2016) showed the positive relationship of benefit receipt with mental health and economic satisfaction. The benefits of social pension also extend to non-recipients in family. Households with higher income security are more likely to migrate elsewhere for a job (Barrientos and Lloyd-Sherlock, 2003), or use the resources to provide better healthcare to their children (Duflo, 2000). The presence of a pensioner was associated with more educational opportunities and nutrition for grandchildren (Case and Menendez, 2007).

Non-contributory pensions have some limitations. First, public income transfers may displace private transfers from children to parents. Some studies argued that public pension transfer would do little to poverty reduction if it substitutes for private income support (Cox and Jimenez, 1989; Juarez, 2009). Second, they may discourage labor supply in old age (Bertrand et al., 2003). Third, they would promote moral hazards in potential beneficiaries and reduce participation in contributory pension programs (Bertranou et al., 2004).

2.3 Method

2.3.1 Data Description

The data for this study comes from 2012 and 2014 waves of the Korean Longitudinal Study of Aging (KLoSA). The KLoSA is a biannual longitudinal survey that has tracked community-dwelling adults aged 45 years or older and their families since 2006. The study is designed to capture various aspects of population aging necessary to understand economic, social, and health situations at the end of life. Survey structures and questions are harmonized with the Health and Retirement Study (HRS).

Households in the KLoSA were selected using multistage stratified sampling based on geographical stratification and housing types. The initial 2006 survey interviewed 10,254 individuals from 6,171 households. Retention rates have been consistently above 85% in the subsequent waves. In 2012 and 2014, the survey re-interviewed 7,486 and 7,029 individuals. The interviews have been administered primarily in the second half of the year, with the 2014 survey conducted over September through November. Since the BOAP reform was implemented in July 2014, comparing 2012 and 2014 waves allows us to examine a short-term and immediate impact of the benefit increase.[1]

Following the previous studies, the sample is limited to respondents aged above 65 in 2014 (Kang and Moon, 2013; Lee et al., 2017). This sample selection excludes respondents who were not age-eligible for the BOAP at the time of reform. Since individual characteristics might substantially differ across age, limiting the sample to age-eligible individuals gives a more homogeneous sample and reduces the potential for omitted variable bias. After excluding observations with missing or miscoded data, the final sample corresponds to the balanced panel of 4,113 individuals.

2.3.2 Measures of Subjective Well-Being

Subjective well-being in the KLoSA is measured over five domains; (a) financial situation, (b) health status, (c) relationship with spouse, (d) relationship with children, and (e) overall quality of life. Before asking the first well-being question, the following instruction is given to solicit assessments relative to the population at the same ages. *Next we would like to ask you a few questions about the quality of life. Please indicate the level of satisfaction with the following things in comparison with peers at the similar ages.*[2] The well-being questions

[1] See the KLoSA website (http://survey.keis.or.kr) for detailed information about survey procedures.

[2] Survey questions are translated from Korean by authors.

run as follows: *How happy are you at present with your (financial situation / health status / relationship with spouse / relationship with your children / overall quality of life)?* The response takes the form of probability and ranges from 0 to 100 in the multiples of 10. Higher values correspond to higher levels of perceived satisfaction. These questions are broadly in line with the life satisfaction questions employed in the earlier studies (Bradburn, 1969; Cantril, 1965).

Empirical analyses consider financial satisfaction, health satisfaction, relationship satisfaction (with children), and overall life satisfaction. Financial satisfaction is expected to capture the direct impact of the pension benefit increase through poverty alleviation. Health satisfaction and relationship satisfaction would capture any indirect influence through increased access to health care or displacement of private income support provided by children. Marital satisfaction is not included in empirical analyses. Income effect on marital relationship is theoretically ambiguous and unlikely to be significant within a few months after the reform. In the preliminary analyses, we estimated the same set of models for marital satisfaction and found no significant association with the BOAP.

2.3.3 Treatment and Control Group

The impact of the expansion in the basic pension benefit is evaluated by comparing pre vs. post-2014 changes in subjective well-being between the treatment and control groups. The control group includes persons above age 65 who did not receive benefits from the BOAP in both 2012 and 2014 (1,395 individuals). Since our sample is limited to age-eligible individuals, this group consists of persons who could not pass the asset-based income test or those who are income-eligible but failed to join the program. The treatment group includes age-eligible individuals with benefits received from the BOAP (2,718 individuals). This is made up of two groups; (a) those who joined the program prior to 2012 and stayed being enrolled in 2014 (1,988 individuals), and (b) individuals who newly joined the program in 2014 (730 individuals). In the new beneficiary group (category b), only 216 individuals became age-eligible in 2014, while 514 individuals were those who could apply for the program in the past. According to our analysis of pre-intervention data, these 514 individuals have not reported a significant drop in their wealth holdings through 2012 and 2014. This indicates that they were eligible for the basic pension benefit prior to 2014 but chose not to opt-in, perhaps because of small expected benefits to justify participation efforts or lack of cognitive skills to go through application process.

2.3.4 Empirical Framework

Since enrollment in the BOAP is voluntary, beneficiaries are likely to be different from the control group in unobserved ways. Under this setting, nave comparison of the enrolled and non-enrolled would capture both treatment and self-selection effect, which yields biased estimate of the policy effect. The preferred approach is then to compare the counterfactual outcome of treated persons to the observed outcomes after being treated. In program evaluation, the average treatment effect on the treated (ATT) is defined as the expected value of the outcome among program participants minus the expected value of the outcome they would have had if they had not participated in the program. The ATT can be expressed as

$$ATT = E(Y_{i1} - Y_{i0}|D_i = 1) = E(Y_{i1}|D_i = 1) - E(Y_{i0}|D_i = 1), \tag{2.1}$$

where i indexes survey participants; D_i is an indicator for program participation; Y_{i1} is the well-being outcome of participant who had benefited from the 2014 expansion of the BOAP; and Y_{i0} is the well-being outcome of the same individual if it had not benefited from the expansion. The major problem is that we do not know what the level of outcomes would have been if individuals had not participated in the BOAP. In the case individual i was treated with the expansion, counterfactual Y_{i0} cannot be observed in data.

Rosenbaum and Rubin (1983) developed the propensity score matching (PSM) approach to approximate counterfactual group. This method use observed characteristics (Z_i) that affect program participation and outcome in the absence of program effect to match participants with non-participants who have similar characteristics. Hence, the program effect is estimated by difference in outcome between participants and matched non-participants, assuming that a matched sample represents counterfactual group (Smith and Todd, 2005). This approach builds on the conditional mean independence assumption, $E(Y_{i0}|Z_i, D_i = 1) = E(Y_{i0}|Z_i, D_i = 0) = E(Y_{i0}|Z_i)$. That is, conditional on observed characteristics, enrollment in the BOAP in 2014 can be treated as random. If this assumption is satisfied, there exists a matched control analogue for each treated individuals, and $E(Y_{i0}|Z_i, D_i = 0)$ can be substituted for $E(Y_{i0}|D_i = 1)$. Since observed characteristics may be large in dimension, matching is performed on a single dimension propensity score, $p(Z_i) = Pr(D_i = 1|Z_i)$. The propensity score is the probability of receiving basic pension benefit conditional on observed characteristics at the individual or household levels (Rosenbaum, 2002). If outcomes are independent of program enrollment conditional on Z_i, they are also independent of $Pr(D_i = 1|Z_i)$ (Rosenbaum and Rubin, 1983). The propensity score is estimated by the probit regression of BOAP enrollment status on Z_i. As a result, the ATT with matching is given by

$$ATT = E(Y_{i1}|D_i = 1) - E(Y_{i0}|p(Z_i), D_i = 0). \tag{2.2}$$

The limitation of PSM is that treatment and control groups are balanced with respect to observed covariates only. If there is any unobserved covariate that correlates with program participation and subjective well-being, the estimate of the policy effect would still be biased. However, the longitudinal structure of the KLoSA allows us to account for, at least, time-invariant differences between treatment and control observations (e.g., personality, attitudes, time preference, etc.). In other words, we can take first differences of the outcomes and thereby removes any variation in time-invariant unobserved characteristics between treatment and control observations. If t and $t + 1$ indicate before and after the expansion of the BOAP benefits (i.e., 2012 and 2014), the difference-in-differences (DD) estimator can be combined with the PSM as follows:

$$ATT = E(Y_{i1}^{t+1} - Y_{i1}^{t} | D_i = 1) - E(Y_{i0}^{t+1} - Y_{i0}^{t} | p(Z_i), D_i = 0). \tag{2.3}$$

While the DD-PSM estimator yields more robust estimates than the PSM (Imbens, 2004), it is still prone to spurious correlation if there are time-varying unobserved covariates that determine selection into treatment and create variation in the outcomes. This study takes advantage of the KLoSA data to control for a wide variety of time-varying determinants.

2.3.5 Matching and Estimation Strategy

The comparison group members for each treated person is chosen according to various measures of proximity. This study employs two matching methods: nearest-neighbor (NN) and Kernel matching. The difference between these methods is the way to define the neighborhood for treated persons and handle common support problem. Under the NN method, each treated individual is matched with persons in the comparison group that are most similar in terms of propensity score. A potential drawback of NN matching is that matching quality could be reduced if the closest neighbor is far away. The NN matching with caliper avoids the risk of bad matches by matching only comparison persons whose propensity score falls within a pre-determined tolerance level. Considering tradeoff between bias and variance, this study uses 5-to-1 and 2-to-1 NN matching with replacement and caliper 0.01.

With Kernel matching, each treated individual is matched with a weighted average of all controls where the weights are inversely proportional to the distance between the treated and controls' propensity scores. The Kernel matching is essentially a weighted regression of the counterfactual outcome on an intercept with Kernel weights being used as regression weights (Smith and Todd, 2005). The choice of threshold distance (bandwidth parameter) is important as the tradeoff between variance and bias arises (Heckman et al., 1997). To show the robustness our estimates, different levels of bandwidths (0.01 and 0.05) are selected. In our preliminary investigtions, the estimation results remained robust to different matching algorithms and parameter settings. These results will be made available upon request. Appendix provides detailed explanation about each matching algorithm.

If we let w_{ij} denotes the weight assigned to matched individual j when compared with treated individual i, Blundell and Dias (2000) show that the ATT in equation (2.3) is estimated by

$$ATT^{DD-PSM} = \frac{1}{N_{D_1}} \sum_{i \in D_1 \cap S} \Big[(Y_{i1}^{t+1} - Y_{i1}^{t}) - \sum_{j \in D_0 \cap S} w_{ij} (Y_{j0}^{t+1} - Y_{j0}^{t}) \Big]. \tag{2.4}$$

where S is the area of joint common support, defined as the subset of treated individuals who are matched with the counterfactual group; D_1 and D_0 denote the treatment and control group; and N_{D_1} is the number of treated individuals who belong to joint common support S. Standard errors are bootstrapped with 50 iterations.

2.3.6 Variable Selection

The covariates in Z_i are selected under two criteria; factors that proxy for asset-based eligibility rules and have an influence on subjective well-being. In principle, only variables that correlate with both participation decision and the outcome variables should be included (Caliendo and Kopeinig, 2008). Since variable selection is arbitrary, we start with an over-parametrized model and exclude regressors that are uncorrelated with either enrollment in the BOAP or the well-being measures. When there are regressors that represent eligibility conditions, they are retained in the regression model regardless of their correlation with enrollment or well-being measures. All covariates are measured before the expansion using the 2012 data to avoid potential endogeneity problems. Specifically, we control for age, gender, education background, marital status, labor supply (retirement status), household income, home ownership, public and private health insurance ownership, self-reported health, activities of daily living (ADL) score, and location of residence. Age is modeled in a quadratic form to eliminate aging effects in the DD design. Education background is captured by indicators for middle school, high school, or college degree, with less than middle school being omitted as a reference group. Marital status takes one if married and zero if separated, divorced, widowed, and never married. Following Bonsang et al. (2012), individuals are classified as being retired if he/she is out of the labor force with the intention of staying out permanently. Household income is the sum of all incomes received by both spouses over the last 12 months, including capital gains, pension income, and benefits from other government welfare programs. Home ownership is included to proxy for the overall volume of wealth. While household wealth in the KLoSA is measured over various domains, we do not utilize such information to avoid the loss of efficiency resulting from measurement error. Our preliminary analysis finds that a binary indicator for home ownership is more predictive of enrollment in the BOAP than a continuous measure of total net worth. This could be because measurement error in wealth reports induces attenuation bias in the coefficient estimate. Self-reported health and ADL score are included to capture changes in health condition and disability status. Since medical expenditure is a major spending category for retirees, those with poor health or disabilities would be more likely to enroll in the BOAP. Lastly, we include an indicator for whether the respondent resides in metropolitan area, middle/small city, or rural area to account for unobserved differences in program participation across regions.

2.4 Results

2.4.1 Propensity Score Estimation and Balancing Properties

Table 2.1 presents sample characteristics prior to matching. The data in panel A is based on a full sample (4,113 individuals) as discussed above. Panel B is limited to respondents with living children (2,137 individuals). Since a question about satisfaction with parents-children relationship was asked to those with living children, panel B is based on a smaller sample. Our analyses present two sets of results throughout the study.

The first three columns in each panel show the mean of each variable in 2012 and corresponding t-test results. On average, persons in the control group are more likely to be younger, male, educated, married, in better health, covered by health insurance, and working in labor force. Annual household income and home ownership are also higher for the control group as most of these persons are above an asset-testing threshold. The average differences in these characteristics between the treatment and control groups are large enough to reject the null hypothesis at the 1% or 5% significance level. These heterogeneities support the PSM as a suitable empirical framework to estimate the treatment effect.

Columns (4) and (8) report probit coefficient estimates of the determinants of the BOAP enrollment. The magnitude and sign of the coefficients are expected in the sense that socioeconomically disadvantaged groups are more likely to participate in the BOAP. The enrollment status exhibits strong correlations with variables related to asset-testing, but not with a measure of health and retirement status. This pattern is consistent with the fact that the BOAP benefits are allocated to the bottom 70% of the income distribution.

Table 2.2 presents a series of test statistics concerning matching quality. First, we compute the median and mean of the absolute standardized bias using unmatched and matched sample (Rosenbaum, 2002). The absolute standardized mean (median) difference is defined as the absolute value of the difference between the weighted mean (median) for treatment group and the weighted mean (median) for the control group divided by the unweighted standard deviation of the treatment group. Second, we estimate a probit model using the matched sample to compare the pseudo R-squared with that obtained from a probit model estimated on the unmatched sample. If covariates are well balanced between the two groups, pseudo R-squared should be reduced very close to zero. Third, a likelihood-ratio test was conducted to test for the joint significance of probit coefficient estimates after matching (Sianesi, 2004).

Irrespective of matching methods, absolute standardized bias is reduced significantly through matching. Mean and median absolute standardized bias in the matched sample does not exceed or is similar to the commonly accepted threshold of 3% or 5% (Caliendo and

Kopeinig, 2008). The next columns show that the pseudo R-squared fell to almost zero after matching. Similarly, the likelihood-ratio test statistics are overall small and fail to reject the null hypothesis at the 10% level (5% level for NN matching in panel A). These test results all point to no systematic difference in the distribution of the covariates between the matched and unmatched sample. The columns at the right-end of the table list the number of observations in the treatment and control group. Because matching is implemented with replacement, only a few observations were discarded.

The average sample statistics and t-values on post-matching sample are presented in Table 2.3. These values are generated by the Kernel matching with 0.01 bandwidth. This matching method is our preferred approach, although using other methods does not result in qualitatively different balancing properties. Columns (3) and (6) report the normalized difference (percentage bias) for each covariate. As shown in balancing test results, matching on observables has been, to a large extent, successful. On all covariates, the normalized difference is well below 25%, meaning that the sample is balanced on covariates. With the exceptions of two variables (retirement status and household income), none of the other variables in the treated individuals are significantly different from persons in the non-treated group.

2.4.2 Impact Estimates

Table 2.4 reports impact estimates of the 2014 expansion of the BOAP on subjective well-being. We have presented two estimates; one based on an unmatched sample and others based on Kernel and NN matching. Looking at the intent-to-treat estimates based on an unmatched sample, there is some evidence of a downward bias in the treatment effect relative to the matched ones. This is because participation rate is lower in relatively wealthy but eligible households where pension benefits account for a small portion of their monthly income. As this group is more pronounced for the control group, their average well-being scores decrease less over time in comparison with those of the matched control group. In double difference framework, this ought to reduce the treatment effect.

For the matched samples, results are very similar across different matching methods. In terms of financial satisfaction, the coefficient estimates of ATT range from 2.21 to 2.63. These estimates are different from zero at the 1% or 5% significance level. Compared to the 2012 sample mean of financial satisfaction in the treatment group (Table 2.9), this represents about 4.8-5.7% increase. Regarding health satisfaction, the estimated ATTs represent approximately 4.5-6.4% statistically significant improvement from the pre-intervention score of 48.46. The next two columns for relationship satisfaction and life satisfaction show the similar positive coefficient estimates. Although the sign of the estimates is in line with our hypothesis, standard error estimates are too large to reject the null hypothesis at the 10% level. Note that a few ATT estimates are statistically significant with NN matching but small in magnitude relative to the pre-intervention level and not robust to matching methods.

2.4.3 Impact Estimates by Subgroups

Of particular interest to policymakers is whether and to what extent policy benefits accrue to specific population subgroups. If the impact of the BOAP is more pronounced for vulnerable populations, it is plausible to say that overall efficacy of the expansion is much greater than the average impact. Table 2.5 shows the heterogeneous effect of the BOAP by age, gender, marital status, and household income. First, results in panel A shows a significant age gradient in the treatment effect. The estimated ATTs are overall much bigger in persons above age 70. Second, across gender the BOAP has a greater impact on women. The impact of the BOAP on financial and health satisfaction is statistically significant for women but not in men. Since labor force participation has been limited in Korean baby-boomers (Lee et al., 2008), small benefits from the BOAP could have a fairly large impact on women's subjective well-being. In panel C, the ATT estimates are only marginally significant in married couples. This could be because the BOAP provides 1.7 times more benefits to married couples than singles. Lastly, we stratify our sample by household income and find expected results for financial, relationship, and life satisfaction. When the outcome is health satisfaction, we discover the opposite pattern in which the policy effect is rather significant for relatively wealthy households but not in those at the bottom 25%. We cannot think of any reason why this relationship arises for health satisfaction. Hence, the remaining explanation is that our models for health satisfaction capture the effect of unobserved factors other than the BOAP. The following investigations show that a violation of parallel trend assumption could contribute to this unexpected results.

2.4.4 Testing for Parallel Trend Assumption

The main identification assumption underlying DD analysis is that trends in subjective well-being between the treatment and control groups are the same prior to the 2014 expansion of the BOAP. If outcomes had trended differently before the expansion, there would have been some unobserved factors other than the BOAP that has created a trend break in subjective well-being. This parallel trend assumption is tested by examining the mean difference in well-being measures between the two groups prior to the expansion. In a regression context, this is evaluated by assessing the significance of the interaction effects involving pre-2014 binary variables. These estimates are shown in Table 2.6 with the year 2012 being omitted as a reference group. For this analysis, we use 2008-2012 waves of the KLoSA and estimate average treatment effects (ATE). This regression model is weighted by Kernel weights with 0.01 bandwidth, which comes from the propensity score estimation using the 2012 data. Since the ATE is not equal to ATT, this approach yields only suggestive evidence.

In column (1), the coefficient estimates of γ_1 and γ_2 are statistically insignificant at the 10% level. The F-test on the joint significance at the bottom panel also fails to reject the null hypothesis. The similar findings can be observed in columns (3) and (4). This suggests that there has been little difference in these outcomes between the two groups during 2008-2010 relative to the 2012 level, and thus the parallel trend assumption holds. In column (2), the estimates of γ_1 are γ_2 are also not significantly different from zero. However, the p-value for F-test is quite close to 0.1, and a trend in health satisfaction estimated by coefficient estimates on year fixed effects and interaction terms shows a clear trend break beginning in 2008 (Figure 2.1). Although this trend break is not statistically significant, it indicates that unobserved factors have had some confounding effect on the ATT estimate to some extent. Hence, we avoid drawing strong inferences from the previous estimates for health satisfaction.

2.4.5 Testing for Anticipatory Effects

The expansion of the BOAP benefits was first proposed in mid-2012 during the presidential primaries of the Korean conservative party. The party's nominee, Park Guen-Hye, who then became the 18th president of South Korea, promised to give between $19-190 additional monthly benefits to all seniors over age 65. Because the 2012 survey was conducted from September to November, respondents in our sample could have predicted upcoming benefit expansion. If they increased consumption and reduced saving in anticipation of the expansion, the base level of well-being in 2012 would have been much higher, and thereby improvements from the 2012 level would be understated. To test for an anticipatory response, we re-estimate the ATTs using 2010 as a base year. Table 2.7 presents the results. In panel A, we compare changes in well-being over 2010 and 2012. If anticipatory effects present, the 2012 level of well-being should be much higher than the 2010 averages. Panel B uses the 2010 and 2014 data to implement similar comparisons. Without having anticipatory changes, coefficient estimates should have similar sign and magnitudes across models. Looking at panel A, we find no evidence that there were improvements in well-being that results from anticipatory effects. In panel B, the pattern in the coefficient estimates remains qualitatively similar to the baseline estimates. These results suggest that anticipation effect is trivial in the study of the BOAP.

2.4.6 Placebo Tests

Table 2.8 presents results from a placebo test that falsely defines an eligible age. We assumed that persons below age 65 become eligible for the BOAP and re-estimated the ATT estimates using 2012 and 2014 surveys. If our previous estimates are created by unobserved factors that have differential impacts on high and low income groups regardless of age, the ATT estimates should also be statistically significant in this hypothetical setting. Since enrollment in the BOAP was not asked in this group, persons with less than 75th percentile household income in the 2012 and 2014 surveys are considered as a treatment group. The analytic sample for this analysis includes 2,803 individuals below age 65, with 1,871 individuals being assigned to the treatment group. The coefficient estimates are not estimated with great precision and carry alternating signs. The null hypotheses are not rejected at the 10% level across different matching methods. Overall, we find no evidence that the previous estimates result from differential trends in well-being across different income levels.

2.5 Conclusion

This study examined the impact of the 2014 expansion of the BOAP benefits on subjective well-being among Korean elderly. Using a matched difference-in-differences approach, we made concerted effort to control for non-random selection into treatment and control groups, as well as differences in time-invariant unobserved characteristics between individuals in both groups. The estimation results show that the reform resulted in an increase of 4.8-5.7% in self-assessed satisfaction with own financial situation. In terms of magnitude, these estimates are approximately 2.5 times larger as compared to the previous studies that examined the introduction of the BOAP in 2008.

This comparison in effect size has a significant implication. Both the BOAP and the reform in 2014 leads to a similar increase in cash transfer, which amounts to $100-130 additional income per month. However, the previous studies based on the 2008 data generally found a small impact of the BOAP, whereas recent estimates exploiting the 2014 reform, such as ours and Lee et al. (2017), reported much larger and economically significant improvements in well-being outcomes. This difference can be attributed two aspects; (a) a lower base income in 2014 as the sample is older than the 2008-based study, and (b) limitations in study design. According to our calculations using KLoSA data, a lower base income does not seem to drive this difference because average household income has decreased only by 12% from 2008 to 2014. As discussed above, unobserved confounders that occurred around 2008 would have had differential impacts on treated and untreated groups and discouraged the estimate of the policy effect. This study calls for further evaluation of the BOAP using the 2014 reform as a natural experiment to yield unbiased policy effect.

We find no evidence of indirect benefits that extend to improved health, parents-children relationship, and overall life satisfaction. The estimates of the health satisfaction effect were positive and statistically significant but seem to result from unobserved confounders occurred before 2014. For relationship and life satisfaction, the estimates show no increase through 2012-2014 or inconsistent evidence that is not robust to different matching methods. Especially noteworthy is our findings on relationship satisfaction. Empirical studies provided mixed evidence on the crowding-out effects of public transfers (Cox and Fafchamps, 2007). In studies of the BOAP, Koh and Yang (2017) showed a complete displacement of private transfer, while Lee et al. (2017) found no such decrease. Since pension benefits would lower a potential conflict between parents and elderly children regarding the duty of financial support, a reduced private transfer would be reflected in improved relationship satisfaction. Our findings of no relationship effect imply that private transfer is not affected by the BOAP.

There is considerable heterogeneity in the impact of the reform across subpopulations. Our sub-group analyses revealed that the increase in financial satisfaction is more pronounced for the more aged, female, and lowest-income populations. We find no differences in financial well-being effect between singles and married couples. These results are consistent with the policy objective to re-distribute economic resources to more vulnerable populations. For overall life satisfaction, none of the subpopulations experienced a significant improvement over the reform.

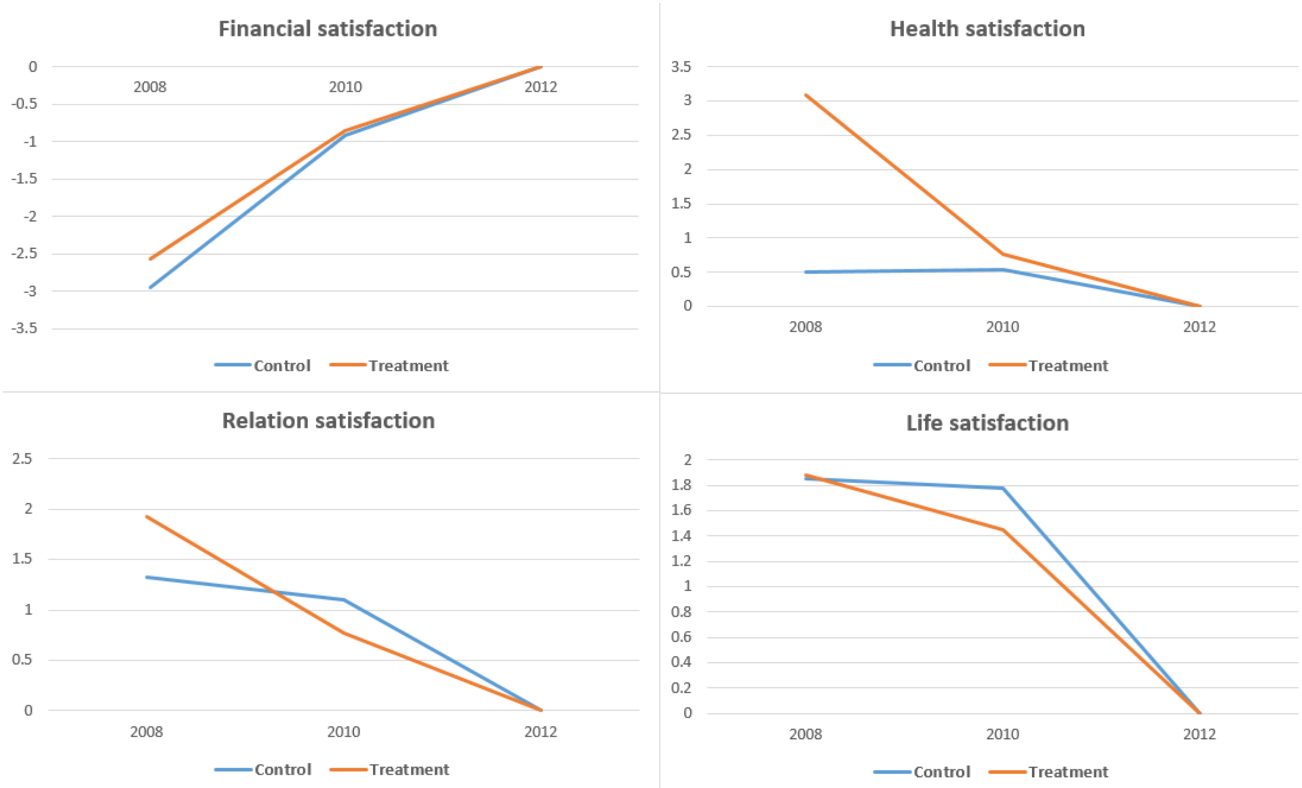

Figure 2.1: Event Study Plots

Table 2.1: Descriptive Statistics before Matching and Propensity Score Probit Estimates

	Panel A: Full sample (N=4,113)				Panel B: Sample with children (N=2,137)			
	Treated group (mean)	Control group (mean)	Difference (1)-(2) (t-values)	Propensity score probit (Coefficients)	Treated group (mean)	Control group (mean)	Difference (1)-(2) (t-values)	Propensity score probit (Coefficients)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Age	74.4	69.8	21.6***	0.394***	75.6	70.4	15.8***	0.412***
Age squared	5579.9	4912.3	21.0***	-0.002***	5757.9	5001.2	15.2***	-0.002***
Female	0.63	0.47	9.81***	0.035	0.74	0.55	8.36***	0.042
Middle school graduate	0.12	0.20	-6.85***	-0.401***	0.11	0.19	-5.22***	-0.389***
HS or college graduate	0.15	0.41	-19.7***	-0.715***	0.11	0.40	-16.2***	-0.814***
Married	0.62	0.85	-15.2***	-0.315***	0.36	0.67	-13.6***	-0.321***
Retired	0.77	0.67	6.38***	-0.046	0.81	0.68	6.66***	0.090
HH income (10,000 won)	1665.2	2595.0	-13.5***	-0.0001***	1720.4	2550.3	-8.95***	-0.0001***
Home ownership	0.79	0.92	-10.3***	-0.547***	0.79	0.90	-6.05***	-0.468***
Public health insurance ownership	0.91	0.97	-7.04***	-0.088	0.91	0.97	-4.76***	-0.134
Private health insurance ownership	0.08	0.23	-13.0***	-0.308***	0.08	0.22	-9.27***	-0.243**
SR health - fair or better	0.56	0.72	-9.72***	-0.021	0.55	0.76	-9.20***	-0.164**
ADL score	0.25	0.15	2.95***	-0.006	0.26	0.10	3.18***	0.011
Urban area	0.39	0.43	-2.45**	-0.049	0.38	0.43	-2.18**	-0.136**
Likelihood ratio χ^2 statistic				992.3				550.7
McFadden's pseudo R^2				0.188				0.217

Notes: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

Table 2.2: Quality of Matching

	Absolute standardized bias				Pseudo R^2		LR ratio		Treated group Observations		Control group Observations	
	Median		Mean									
	Before	After	Before	After	Before	After	Before	After	Before	After	Before	After
Panel A: Full sample												
K (b=0.01)	34.2	1.0	37.6	1.5	0.188	0.002	992.3	14.0	2,718	2,712	1,395	1,395
K (b=0.005)	34.2	1.6	37.6	1.9	0.188	0.002	992.3	16.2	2,718	2,712	1,395	1,395
N (k=2, δ=0.01)	34.2	1.9	37.6	2.2	0.188	0.003	992.3	22.5	2,718	2,712	1,395	1,377
N (k=5, δ=0.01)	34.2	2.0	37.6	2.3	0.188	0.003	992.3	22.3	2,718	2,712	1,395	1,377
Panel B: Sample with children												
K (b=0.01)	39.8	1.8	42.4	2.6	0.217	0.003	550.7	12.7	1,537	1,526	600	581
K (b=0.005)	39.8	2.1	42.4	2.9	0.217	0.003	550.7	14.4	1,537	1,526	600	581
N (k=2, δ=0.01)	39.8	2.2	42.4	2.8	0.217	0.004	550.7	16.6	1,537	1,526	600	581
N (k=5, δ=0.01)	39.8	3.1	42.4	3.0	0.217	0.004	550.7	15.8	1,537	1,526	600	581

Notes: Matching methods; K, kernel; N, nearest-neighbor. b refers to bandwidth for kernel matching. k refers to the number of nearest neighbor matches involved. δ refers to the size of caliper. All matching is with replacement and on the common support.

Table 2.3: Covariate Balance After Matching

	Panel A: Full sample (N=4,107)				Panel B: Sample with children (N=2,107)			
	Treated group (mean)	Control group (mean)	Percentage bias (%)	Difference (1)-(2) (t-values)	Treated group (mean)	Control group (mean)	Percentage bias (%)	Difference (1)-(2) (t-values)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Age	74.4	74.5	-1.0	-0.37	75.5	75.6	-1.5	-0.41
Age squared	5577.5	5584.8	-0.8	-0.27	5750.4	5764.4	-1.4	-0.37
Female	0.63	0.62	0.9	0.35	0.73	0.73	0.5	0.14
Middle school graduate	0.12	0.12	0.8	0.32	0.11	0.11	0.3	0.10
HS or college graduate	0.15	0.14	1.1	0.51	0.11	0.11	0.7	0.27
Married	0.62	0.63	-2.3	-0.74	0.36	0.38	-4.4	-1.19
Retired	0.77	0.78	-3.8	-1.50	0.81	0.84	-6.5	-2.03**
HH income (10,000 won)	1647.3	1730.3	-3.9	-1.87*	1727	1705.6	1.1	0.34
Home ownership	0.79	0.80	-3.1	-0.98	0.80	0.80	-1.9	-0.48
Public health insurance ownership	0.91	0.91	0.4	0.14	0.91	0.92	-3.6	-0.87
Private health insurance ownership	0.09	0.08	0.4	0.17	0.08	0.07	1.7	0.64
SR health - fair or better	0.57	0.56	0.7	0.23	0.55	0.58	-5.7	-1.47
ADL score	0.25	0.25	-0.1	-0.03	0.25	0.23	2.6	0.66
Urban area	0.39	0.40	-1.9	-0.69	0.38	0.40	-4.6	-1.27

Notes: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

Table 2.4: ATT Estimates

Outcome:	Financial satisfaction (1)	Health satisfaction (2)	Relationship satisfaction (3)	Life satisfaction (4)
Unmatched	1.23 (0.62)**	1.40 (0.68)**	1.03 (0.84)	1.07 (0.58)*
K (b=0.01)	2.34 (0.80)***	2.17 (0.98)**	1.64 (1.04)	1.07 (0.79)
K (b=0.005)	2.44 (0.73)***	2.31 (0.97)**	1.61 (1.07)	1.03 (0.70)
N (k=2, δ=0.01)	2.21 (1.09)**	3.11 (1.07)***	1.59 (1.30)	1.46 (0.68)**
N (k=5, δ=0.01)	2.63 (0.97)***	2.65 (0.87)***	1.80 (1.14)	1.41 (0.78)*

Notes: Matching methods; K, kernel; N, nearest-neighbor. b refers to bandwidth for kernel matching. k refers to the number of nearest neighbor matches involved. δ refers to the size of caliper. Standard errors in parentheses are bootstrapped with 50 iterations. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

Table 2.5: Heterogeneous Effect of the BOAP

Outcome:	Financial satisfaction	Health satisfaction	Relationship satisfaction	Life satisfaction
	(1)	(2)	(3)	(4)
Panel A: stratified by age				
Age ≤ 70	-0.37 (1.24)	0.97 (1.21)	-1.48 (1.65)	0.17 (0.96)
Age > 70	2.77 (1.14)**	2.17 (1.31)*	1.90 (1.25)	1.17 (1.04)
Panel B: stratified by gender				
Female	3.19 (1.11)***	2.74 (1.23)**	0.49 (1.40)	1.15 (0.84)
Male	0.98 (0.99)	0.78 (1.59)	4.58 (1.99)**	1.81 (1.11)
Panel C: stratified by marital status				
Married	1.77 (1.01)*	1.78 (0.96)*	0.53 (1.60)	0.98 (0.70)
Not married	1.50 (2.20)	1.42 (2.43)	1.31 (1.48)	0.88 (1.63)
Panel D: stratified by household income				
HH income $\leq Q_1$	4.25 (1.89)**	-0.47 (2.06)	2.86 (2.13)	3.10 (1.80)*
HH income $> Q_1$	1.68 (0.93)*	3.23 (1.04)***	1.04 (1.23)	0.56 (0.83)

Notes: ATT estimates from kernel matching with 0.01 bandwidth. Standard errors in parentheses are bootstrapped with 50 iterations. Not married includes separated, divorced, widowed, and never married. Q_1 is the first quartile of household income. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

Table 2.6: Tests of Parallel Trend Assumption, ATE Estimates

Outcome:	Financial satisfaction (1)	Health satisfaction (2)	Relationship satisfaction (3)	Life satisfaction (4)
Treated	-3.15 (1.22)**	1.68 (1.50)	1.53 (1.43)	0.87 (1.00)
Year 2008	-2.95 (0.95)***	0.51 (0.92)	1.32 (1.38)	1.85 (0.83)**
Year 2010	-0.91 (0.87)	0.53 (0.70)	1.10 (1.70)	1.78 (0.83)**
γ_1: Treated × Year 2008	0.39 (1.18)	2.58 (1.82)	0.60 (1.67)	0.03 (1.08)
γ_2: Treated × Year 2010	0.05 (1.04)	0.23 (1.38)	-0.33 (1.90)	-0.33 (0.99)
Observations	11,856	11,859	5,115	11,856
Linear restriction (p-values):				
H_0: γ_1=γ_2=0	0.941	0.172	0.862	0.928

Notes: ATE estimates using weights from kernel matching with 0.01 bandwidth. Year 2012 dummy is omitted as a base category. Standard errors in parentheses are clustered at the individual levels. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

Table 2.7: Testing for Anticipatory Effects, ATT Estimates

Outcome:	Financial satisfaction (1)	Health satisfaction (2)	Relationship satisfaction (3)	Life satisfaction (4)
Panel A: wave 3 $\rightarrow$ wave 4				
K (b=0.01)	-0.57 (0.85)	0.62 (0.77)	-0.02 (1.15)	-0.06 (0.81)
K (b=0.005)	-0.44 (0.86)	0.57 (0.78)	-0.14 (1.17)	-0.01 (0.82)
N (k=2, δ=0.01)	0.40 (0.94)	0.68 (0.84)	0.12 (1.26)	0.40 (0.91)
N (k=5, δ=0.01)	-0.51 (0.89)	0.58 (0.79)	-0.06 (1.19)	-0.22 (0.84)
Panel B: wave 3 $\rightarrow$ wave 5				
K (b=0.01)	2.03 (0.98)**	3.49 (1.09)***	1.87 (1.42)	1.69 (0.92)*
K (b=0.005)	2.05 (0.99)**	3.36 (1.10)***	1.77 (1.44)	1.66 (0.93)*
N (k=2, δ=0.01)	1.70 (1.09)	3.04 (1.21)**	1.99 (1.53)	1.28 (1.01)
N (k=5, δ=0.01)	2.14 (1.03)**	3.29 (1.13)***	1.72 (1.46)	1.35 (0.95)

Notes: Matching methods; K, kernel; N, nearest-neighbor. b refers to bandwidth for kernel matching. k refers to the number of nearest neighbor matches involved. δ refers to the size of caliper. Standard errors in parentheses are bootstrapped with 50 iterations. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

Table 2.8: Placebo Tests, ATT Estimates

Outcome:	Financial satisfaction	Health satisfaction	Relationship satisfaction	Life satisfaction
	(1)	(2)	(3)	(4)
Limited to age below 65, treated group = HH income less than 75th percentile in wave 4 and 5				
K (b=0.01)	0.47 (1.99)	-0.64 (1.86)	2.28 (2.76)	0.24 (1.76)
K (b=0.005)	0.30 (2.05)	-0.67 (1.91)	2.00 (2.79)	-0.07 (1.81)
N (k=2, δ=0.01)	-0.28 (2.44)	-0.38 (2.30)	2.23 (2.91)	-0.69 (2.18)
N (k=5, δ=0.01)	0.41 (2.23)	-0.80 (2.10)	2.36 (3.02)	-0.92 (1.95)

Notes: Matching methods; K, kernel; N, nearest-neighbor. b refers to bandwidth for kernel matching. k refers to the number of nearest neighbor matches involved. δ refers to the size of caliper. Standard errors in parentheses are bootstrapped with 50 iterations. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

Table 2.9: Mean Differences Before and After Matching

Outcome:		Financial satisfaction		Health satisfaction		Relationship satisfaction		Life satisfaction	
		Treated	Control	Treated	Control	Treated	Control	Treated	Control
Unmatched	Before	46.01	60.44	48.43	58.54	65.06	70.65	54.61	63.48
	After	45.26	58.46	48.61	57.32	64.12	68.68	54.54	62.34
	Diff.	-0.75	-1.98	0.18	-1.22	-0.94	-1.97	-0.07	-1.14
K (b=0.01)	Before	46.04	55.91	48.46	51.46	65.20	67.33	54.65	58.68
	After	45.25	52.79	48.60	49.44	64.18	64.67	54.53	57.49
	Diff.	-0.79	-3.12	0.14	-2.02	-1.02	-2.66	-0.12	-1.19
K (b=0.005)	Before	46.04	55.85	48.46	51.42	65.20	67.42	54.65	58.67
	After	45.25	52.62	48.60	49.25	64.18	64.80	54.53	57.52
	Diff.	-0.79	-3.23	0.14	-2.17	-1.02	-2.62	-0.12	-1.15
N (k=2, δ=0.01)	Before	46.04	55.88	48.46	52.05	65.20	68.08	54.65	59.30
	After	45.25	52.88	48.60	49.09	64.18	65.48	54.53	57.72
	Diff.	-0.79	-3.00	0.14	-2.96	-1.02	-2.60	-0.12	-1.58
N (k=5, δ=0.01)	Before	46.04	56.16	48.46	51.64	65.20	67.52	54.65	58.97
	After	45.25	52.74	48.60	49.14	64.18	64.70	54.53	57.44
	Diff.	-0.79	-3.42	0.14	-2.50	-1.02	-2.82	-0.12	-1.53

Notes: Matching methods; K, kernel; N, nearest-neighbor. b refers to bandwidth for kernel matching. k refers to the number of nearest neighbor matches involved. δ refers to the size of caliper.

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Chapter 3

Essay II: Secondhand Smoke Exposure and Cognitive Performance in South Korean Elderly Population

3.1 Introduction

The relationship between cigarette smoking and cognitive functioning remains unclear. Research suggests that smoking has both protective and adverse impact on cognition (Hill and Seelert, 2000). Cigarette smoking has been shown to improve cognitive performance by delivering nicotine and stimulating central nervous system in the brain (Swan and Lessov-Schlaggar, 2007). Nicotine is a psychoactive substance that stimulates cholinergic system, and modulate the release of neurotransmitters involved in cognitive functions including dopamine and serotonin (McGehee and Role, 1995). Nicotinic stimulation appears to operate with the activation of parietal cortex, which is essential for psychomotor functions such as visual attention, arousal, and motor activation (Lawrence et al., 2002). Although the cognitive-enhancing effect of nicotine has been controversial (Heishman, 1998), studies on the acute administration of nicotine through gum, injection, nasal sprays, and skin patches report significant improvement in attention (alertness and orientation) and mnemonic function (episodic and working memory) (Heishman et al., 2010; Perkins et al., 1990; West and Jarvis, 1986).

Some studies find that chronic smoking is linked to cognitive deficits and an increased risk of memory-related disease in later life. Long-term continuous smoking is known to promote fatty acids concentration, high blood pressure, and hyperlipidemia, and gradually compromise cardiovascular capacity and efficiency (Winniford, 1990). These conditions reduce cerebral blood flow (Kubota et al., 1987), and result in the deficiency of oxygen and nutrients reaching the brain (Aliev et al., 2003). While temporary oxygen deficit has limited impact, damage over the extended period results in brain shrinkage and manifest as a vascular cognitive impairment (de la Torre, 2002). A recent meta-analysis finds that current smokers exhibit a much faster cognitive decline than subjects who have never smoked, and have 40%-80% higher risk of developing Alzheimers disease and vascular dementia (Anstey et al., 2007).

Nicotine is often delivered by secondhand smoke, and even limited exposure to cigarette smoke results in enough nicotine accumulation in nonsmokers (Brody et al., 2011). Given the toxicity of environmental tobacco smoke exposure (Barnoya and Glantz, 2005; Eisner et al., 2007), few studies delved into the potential impact passive smoking has on cognitive functioning. A study of British population finds that nonsmokers with high levels of salivary cotinine perform are more likely to perform in the lowest 10% on neuropsychological tests as compared to those with low salivary cotinine (Llewellyn et al., 2009). Association of secondhand smoke exposure with mild cognitive impairment or poor cognitive performance is repeatedly reported in a Chinese and Italian sample (Chen et al., 2013a; 2013b; Orsitto et al., 2012). Similar to direct smoking, cardiovascular mortalities are shown to magnify the risk of dementia attributable to indirect nicotine absorption (Barnes et al., 2010).

To date, a majority of evidence on the cognition-enhancing effect of smoking is drawn from mentally incapacitated subjects in which nicotinic stimulation is likely to have a positive influence (Newhouse et al., 2004). While some studies find a modest doseresponse relationship between tobacco use and cognition in unimpaired subjects (Hill et al., 2003; Richards et al., 2003; Wang et al., 2010), their findings are subject to nicotine withdrawal effect in which cognitive benefits are created by a compensating mechanism for transient nicotine deprivation during a survey. Furthermore, longitudinal studies in this context have been sparse and produced mixed results (Chen et al., 2003; Ford et al., 1996; Hebert et al., 1993; Nooyens et al., 2008; and Richards et al., 2003). A recent longitudinal evidence shows that smoking-cognition correlations turn from negative into positive when accounting for unobserved individual-specific effects, and smoking is a significant between-group variable favoring current smokers on cognitive performance over former smokers (Ayyagari and Kessler, 2015). Their findings raise a question of whether the previous evidence captures smoking effect *per se*, or is driven by individual characteristics that determine both smoking initiation/cessation and cognitive performance.

While exploiting the longitudinal structure of data yields more convincing evidence, omitted variable bias is still present if there are unobserved factors that vary with changes in cognition and smoking history over time. For instance, smoking is a well-known risk factor for cardiovascular and pulmonary diseases, and a review of the literature shows a strong association between these conditions and the risk for cognitive impairment (Hill and Seelert, 2000). Retirement is known to accelerate cognitive decline by lowering investment in human capital (Bonsang et al., 2012), and often induces a significant change in smoking and drinking behaviors (Henkens et al., 2008). To rule out individual-level confounders that may bias smoking effect, this study examines the impact of secondhand smoke on the partner's cognitive functioning among married couples. Given that determinants of one spouse's smoking behavior are generally uncorrelated with the other partner's cognitive performance, our modeling strategy produces estimates that are plausibly independent of individual-level unobservables that change over time. Although family-level characteristics that are common to both spouses still affect our estimates and reverse causality remains unaddressed, this is the first population-based longitudinal study to examine secondhand smoke as a predictor of cognitive functioning.

Using data from the Korean Longitudinal Study of Aging (KLoSA), we find that the wives living with smoking husband score higher on the Mini-Mental State Examination than those whose husband is past smokers. Further analyses show that this relationship is robust to the inclusion of household characteristics and the wife' mortality outcomes that could trigger husbands to stop smoking. Overall, our findings are consistent with the evidence on nicotine as a cognitive enhancer.

3.2 Method

3.2.1 Data Description

The data for this study comes from 2006 through 2014 waves of the Korean Longitudinal Study of Aging (KLoSA). The KLoSA is a biannual longitudinal survey that has tracked community-dwelling adults aged 45 years or older and their families since 2006. The study is designed to capture various aspects of population aging necessary to understand economic, social, and health situations at the end of life. Survey structures and questions are harmonized with the Health and Retirement Study (HRS).

The initial 2006 survey interviewed 10,254 individuals from 6,171 households. Households were selected using multistage stratified sampling based on geographical stratification and housing types. The second and third wave in 2008 and 2010 followed up with 8,688 and 7,920 subjects, representing 86.6% and 80.3% of the original panel. The fourth and fifth wave in 2012 and 2014 interviewed 7,486 and 7,029 subjects with the response rates of 73.0% and 68.5%.[1]

The sample for analysis is restricted to respondents older than 75 to obtain a relatively homogeneous sample (33,812 observations). Because smoking shortens lifespan by at least 10 years (Jha et al., 2013), heavy smokers are supposed to be under-represented in the older age group while nonsmokers are over-represented. If smoking delays cognitive aging as hypothesized, estimates of smoking effect will be biased downward in the full sample including the oldest old. Therefore, we drop respondents above age 75 where the smoking effect is significantly attenuated in the preliminary analysis. Next, we exclude respondents for whom the information regarding covariates are missing (31,805 observations). The observations removed at this step include 1,130 observations with proxy responses.[2] Lastly, respondents

[1]See the KLoSA website (http://survey.keis.or.kr) for detailed information about survey procedures.

[2]When a respondent gives more than a threshold number of "don't know" responses or takes unusually long time in the first section, a household member most familiar with the respondent is interviewed as a proxy informant. Disability and mental incapacity may be a reason for the

with only one observation during the survey period are excluded in order for our regression models to exploit within-individual variation. The final sample corresponds to an unbalanced panel of 30,397 observations from 7,296 individuals. Table 3.1 tabulates sample characteristics by smoking status.

3.2.2 Measures of Smoking

Smoking status is categorized into ever smoker and nonsmoker based on the response to a question about current cigarette smoking status. The ever smokers were further asked at what age they began smoking, whether they are currently smoking, at what age they quit smoking, and how many cigarettes on average they had smoked or still smoked per day. The primary measure of interest is a categorical variable concerning their smoking status: current, past, or never. Current and past smokers combine for 18% and 13% of the final sample with a lower prevalence in the later waves.

We also define a composite score of pack-years to reflect smoking intensity. The score is obtained from the number of cigarettes smoked per day divided by 20 (i.e., the number of cigarettes per pack) times years of smoking (Galanis et al., 1997; Schinka et al., 2002). In this calculation, 1 pack-year corresponds to 1 year of smoking 20 cigarettes per day. To account for the high skewness of this composite score, we collapse the pack-year data into deciles and categorize adjacent deciles with similar risk for dementia into four groups: (a) light smoker (pack-year deciles 1-3), (b) moderate smoker (pack-year deciles 4-6), (c) heavy smoker (pack-year deciles 7-8), and (d) very heavy smoker (pack-year deciles 9-10) (Wang et al., 2010). The mean pack-years is 27.8 for current smokers and 33.0 for former smokers.

3.2.3 Measures of Cognitive Functioning

Cognitive abilities are assessed by the Korean Mini-Mental State Examination (K-MMSE). The MMSE is a brief screening test for dementia and has been used to evaluate

unavailability of the main respondent. This implies that persons with severe cognitive impairment could be under-represented in a final sample.

the severity and progression of cognitive impairment (Folstein et al., 1975). The K-MMSE includes 19 items that assess multiple domains of cognitive functioning, such as orientation to time (5 points), orientation to place (5 points), attention and calculation (5 points), registration of three words (3 points), recall of three words (3 points) language (8 points), and visual construction (1 point). While attention/calculation is measured by both serial 7s and spelling "world" backward in the original MMSE, the Korean version test administers only serial 7s to minimize potential language effect (Espino et al., 2004). Moreover, orientation is divided into time and place domain, and visual construction is separated from language items. The total K-MMSE score ranges from 0 to 30 point (K-MMSE 30, hereafter) with a high score representing better global cognitive performance. A cutoff of 23/24 has been typically used in screening for dementia using K-MMSE 30 (Kang et al., 1997).

Studies on individual MMSE items find that cognitive impairment is more pronounced in attention/calculation, delayed recall, and orientation to time, whereas errors rarely occur for immediate recall, language, and orientation to place (Bleecker et al., 1988; Galasko et al., 1990; Magaziner et al., 1987; Tombaugh and McIntyre, 1992). Analyses for demented subjects show a higher percentage of errors and a faster age-related decline in time awareness and ability to recall than in other cognitive domains (Solfrizzi et al., 2001; Tombaugh and McIntyre, 1992). On the other hand, there has been only limited evidence on declining verbal and visuospatial functioning even at the later life (Almkvist and Backman, 1993; Herlitz et al., 1995). These findings imply that the effect of smoking might be significantly greater on particular domains that are prone to non-aging factors. Therefore, we define the alternative summary scores that exclude language and visual construction score. The registration and recall of three words combine for episodic memory score on a 0-10 scale, and this score is summed with orientation to time and attention/calculation to create a 14-point summary score (K-MMSE 14, hereafter). The mean of K-MMSE 30 and K-MMSE 14 are 26.7 and 11.8, respectively.

3.2.4 Estimation

This study employs a fixed effects model to estimate the association between passive smoking and cognitive functioning independent of unobserved individual-specific factors that may influence both smoking behavior and outcome variable. Our empirical analysis is divided into two parts. First, in order to benchmark our results to earlier studies we conduct individual-level analyses in a similar spirit of Ayyagari and Kessler (2015). The smoking effect is identified by comparing changes in the cognitive functioning of current smokers to that of past smokers. While several previous studies examined the difference between current and never smokers, such approach fails to account for unobserved determinants for smoking initiation/cessation that are common to current and past smokers. Since never smokers might be different from current/past smokers in unobserved ways, analyzing a full sample may increase the potential for omitted variable bias. Second, we estimate models for the wife's or non-smoking partner's cognition using the characteristics of both spouses as predictors. Smokers in our sample are predominantly male (smoking prevalence in males=38.7% and females=2.4%), and therefore the impact of the wife's smoking on the husband could not be reliably estimated. These second set of regression models are estimated on the households where both spouses are between age 45 and 75, and at least one spouse is a former or current smoker.

We estimate several variants of the following model for individual i's cognitive functions at time t,

$$y_{i,t} = \alpha + \beta s_{i,t} + \sum_{j=1}^{m} \gamma_j X_{i,j,t} + \nu_i + \varepsilon_{i,t}, \tag{3.1}$$

where $y_{i,t}$ is one of the cognition scores of the wife or non-smoking spouse; $s_{i,t}$ is binary indicators for current smoker and past smoker in reference to never smoker; and $X_{i,j,t}$ is a vector of individual-level confounders measured separately for the husband and wife. The error term consists of a time-invariant person-specific component ν_i and a classical error term with assumptions that $E(\varepsilon_{i,t}) = 0$ and $Var(\varepsilon_{i,t}) = \sigma_{\varepsilon}^2$. Consistency of the coefficient estimates requires, $E(\nu_i | s_{i,t}, X_{i,j,t}) = 0$, which is violated whenever ν_i is correlated with any of the regressors. It can be seen from the above specification that failing to include time-varying confounders in $X_{i,j,t}$ leads to inconsistent coefficient estimates unless the omitted variables are perfectly uncorrelated with the regressors.

A vector $X_{i,t}$ includes age and age squared, health indicators, lifestyle indicators, employment status, and a learning effect indicator. Age and its squared term allow cognitive skills decline at an increasing rate with the aging process. Health indicators include 5-category self-rated health and binary variables for chronic conditions such as high blood pressure, diabetes, heart disease, stroke, and psychiatric problem. Lifestyle is captured by obesity, exercise, and current drinking status that may affect cognitive functioning through changes in physical health. A learning effect indicator represents how many cognition tests respondents have answered to date. This variable nets out any potential learning effect in the evaluation of cognition that results from using a same survey instrument over the interviews. Controlling for employment outcome is to reflect a decrease in cognitive ability and smoking prevalence at the time of retirement (Bonsang et al., 2012; Henkens et al., 2008; Mazzonna and Peracchi, 2012). All regression models include year-of-survey and province fixed effects. Year dummies capture a secular time trend in cognition, and province dummies account for unobserved differences across provinces that are fixed over time.

The fixed effects estimation strategy identifies smoking effect through *changes* in an individual's smoking status over time. To difference out the effect of between-individual heterogeneity, we demean the regressors using the within transformation and set up the following regression model.

$$y_{i,t} - \overline{y_i} = \alpha + \beta(s_{i,t} - \overline{s_i}) + \sum_{j=1}^{m} \gamma_j (X_{i,j,t} - \overline{X_{i,j}}) + (\varepsilon_{i,t} - \overline{\varepsilon_i}) \tag{3.2}$$

The estimates are obtained from OLS regression of $y_{i,t} - \overline{y_i}$ on the demeaned regressors. To decide between the fixed effects and random effects model, we run a Hausman specification test against the null hypothesis that the coefficients estimated by the (efficient) random effects estimator are the same as the ones estimated by the (consistent) fixed effects estimator. All the test statistics presented in the following section point to the FE model as an appropriate estimation technique.

Although the FE coefficients absorb all the unobserved individual heterogeneity, this estimation strategy is subject to a few well-known problems. First, as discussed above the FE estimates are biased and inconsistent if there are omitted time-varying factors that correlate with the changes in smoking status and cognitive ability over the same period. While analyses for married couples greatly reduce this concern, one might argue that there are still unobserved household-level characteristics that have a different influence on husband and wife and thereby inducing spurious correlations between husband's smoking and wife's cognition. Second, even if the model is fully specified the model does not lend itself to causal interpretation due to a potential feedback effect. For instance, severe cognitive impairment could have affected smoking behavior by interfering with daily activities or promoting nursing home entry. Third, the parameters in the FE model are identified by within-individual variations between survey waves. Since the KLoSA has been conducted every other year, the long-term lagging effect of smoking through worsening cardiovascular health or other pathways is captured by the intercepts and hence is not reflected in the estimate of smoking effect in equation (3.2). Any estimate of cognition-smoking correlation in our study represents relatively short-term association within a 2-year period.

3.3 Results

Tables 3.2 and 3.3 report estimation results from individual-level analyses of cognition-smoking correlation. The estimates are obtained from a regression of (demeaned) cognitive functioning on own (demeaned) characteristics in a manner similar to equation (3.2). Table 3.2 includes the baseline regression results for the full sample of 30,397 observations. The models in Table 3.3 re-fit the model after excluding never smokers who might be different from current/past smokers in unobserved ways. Throughout the study, our preferred empirical investigation strategy is to estimate equation (3.2) on ever smokers (individual-level analyses) or married couples where both spouses are ever smoker (household-level analyses).

Table 3.2 reports OLS coefficient estimates on current and past smoking status as well as other determinants of cognitive functioning. The outcome of interest is global cognitive functioning scored by K-MMSE 30, K-MMSE 14, and episodic memory (i.e., the sum of immediate and delayed recall). Given that some domains of cognitive functioning decline slowly over time and fixed effects model utilize within-person variation, our analyses explore the association between a total cognitive ability and smoking.

Across the three specifications, most of the regressors are significantly associated with cognitive functioning, and estimated coefficients carry the intuitive signs. The results show that conditional on the covariates, cognitive functioning (a) declines at an increasing rate with age, (b) decreases with poor physical and mental health, and (c) increases with active lifestyle such as doing regular exercise and working for wages. As reported in the epidemiology literature, stroke and poor mental health seem to carry a significant decline in cognitive functioning whereas other chronic conditions have only limited influence. The coefficient estimates on current and past smoking are generally positive except for episodic memory. However, these coefficients are not estimated with great precision to reject the null hypothesis at the 5% significance level. Overall, we do not confirm the previous evidence that current smokers exhibit worse cognitive functioning than never smokers after accounting for individual heterogeneity and time-varying characteristics. Notice that the coefficient estimates on current smoking are much larger than those on past smoking. Testing the equality of these two coefficients show that current smokers perform significantly better on cognition test than past smokers, and this difference is significant at the 5% level.

Table 3.3 presents estimation results based on 9,475 observations from 2,363 ever smokers. The estimates on the covariates are omitted for brevity. As shown in Table 3.2, coefficient estimates in panel A show that global cognition scores are significantly higher among current smokers compared to former smokers. Our preferred specification in column (1) indicates that smoking is associated with 0.219 points higher K-MMSE 30 score on a 0-30 scale. Evaluated at the sample mean of K-MMSE 30 in ever smokers (=27.07), this corresponds to about 0.8% increase, which is small but certainly not negligible relative to other determinants. For instance, this effect size is as large as the impact of exercise and employment status. The next two columns show the same pattern with positive coefficient estimates, which are significant at the 10% level.

In panel B, we examine whether the positive effect of smoking on cognition is partially offset by the negative smoking effect through poor cardiovascular health. The regression models introduce a binary variable for having been diagnosed with high blood pressure, diabetes, heart disease, and stroke, and its interaction term with current smoking status as the additional predictors. The estimation results offer limited support for such claim. The coefficients on the interaction terms alternate between positive and negative, and are not different from zero at the 5% significance level. These estimates seem to show that cardiovascular disease is not a pathway through which cigarette smoking exerts an indirect influence on cognitive function. Notice that these estimates are specific to the context of this study, and thus they should not be interpreted as the findings that contradict with the previous evidence. Panel B only suggests that indirect negative impact of smoking in our study has limited influence on the positive smoking effect reported in panel A and Table 3.2. As discussed above, the structure of data and estimation method do not allow us to investigate any longer-term effect via worsening cardiovascular health.

Panel C uses information on pack-years to compare cognitive functioning by smoking intensity. We argue that the potential benefits of smoking might be limited to the moderate degree of smoking while heavy smoking still leads to a reduction in cognitive functioning. Smoking intensity is captured by a categorical variable representing light smoker (pack-year deciles 1-3), medium smoker (pack-year deciles 4-6), heavy smoker (pack-year deciles 7-8), and very heavy smoker (pack-year deciles 9-10). The binary indicators for this categorical variable (in reference to light smoker) are controlled for on behalf of a current smoking dummy in the regression model. The sample for this analyses is reduced to respondents who answered a question about the number of cigarettes smoked per day. These include 5,742 observations from both current and former smokers with no missing information on smoking intensity. The coefficient estimates on moderate smoker are positive and different from zero at the 10% level in columns (1) and (2). Other coefficient estimates on heavy smoker and very heavy smoker are negative but statistically insignificant. While we find no conclusive evidence of the benefits and adverse impact of smoking depending on smoking intensity, it could be due to the inflation of the standard error estimates associated with a smaller sample size and the modest number of cigarettes smoked per day in our older subjects.

Tables 3.4-3.6 examine the association of secondhand smoke with the partner's cognitive functioning. Among 13,425 households where both spouses responded to the survey, we select 8,576 households in which both spouses are ever smoker. This sample is then restricted to 6,730 observations with no missing values in the covariates and both spouses between age 45 and 75. Dropping households with only one observation leads to the final sample of 6,443 households over the five survey waves.

Table 3.4 shows the estimated coefficients on smoking adjusted for the husband's and wife's characteristics. Column (1) utilizes the full sample, and column (2) further limits to households where the wife is currently not smoking. We assume that the impact of secondhand smoke on cognition is better identified by examining non-smoking partner's cognitive functioning. Intuitively, the coefficient estimate on the husband's smoking might be underestimated when the model also captures own smoking effect. In column (3), we estimate the model for nonsmoker's cognitive functioning using an indicator for household smoking status as a predictor. A regressor of interest is coded 1 if any spouse within a family is a current smoker and 0 otherwise. The outcome variable is assigned the husband's cognition score if a wife is the only current smoker, or assigned the wife's cognition score if a husband is the only current smoker or both spouses are not current smoker (i.e., past smoker). This approach estimates the impact of secondhand smoke on nonsmoker's cognitive functioning without taking gender effect into account. Across all three specifications, the coefficient estimates on the secondhand smoke are positive and significantly different from zero at the 1% significance level. The effect size evaluated at the sample mean ranges from 1.4% to 1.7%, which are significantly larger than the previous estimates from individual-level analyses.

We conduct robustness test in Table 3.5 by dropping specific subsamples where smoking cessation could be induced by feedback effect or unobserved time-varying household characteristics. First, notice that the husbands in our sample may have quit smoking in response to the wife' mortality outcomes. Since secondhand smoke exposure is associated with the development of certain disease among never smokers (Brennan et al., 2004; Raupach et al., 2006), an altruistic husband could have quit smoking to preserve their wife's health. This potential feedback effect is addressed by excluding a certain subgroup in which smoking-cognition correlations can be created by such mechanism. We use a smoking indicator and health outcomes to identify households in which husband's smoking status changes with wife's mortality outcomes. The sample in panel A exclude households where the husband quit smoking when the wife self-assessed their health poor/fair. Panel B drops households where a wife is diagnosed with a vascular disease (e.g., high blood pressure, diabetes, heart disease, and stroke) since the previous interview. Comparing estimates based on specific subgroups with the results in Table 3.4 will show to what extent such bias affects our estimates on secondhand smoke effect. Second, there could be unobserved household characteristics that correlate with the husband's smoking behavior and wife's cognition. For instance, economic hardship has been shown to impair mental health (McInerney et al., 2013) and depression is known to carry mild cognitive impairment (Panza et al., 2010; Steffens et al., 2006). Household economic conditions such as income and net worth are also well-known predictors of smoking prevalence. These findings raise the concern that financial hardship may affect the husband's smoking and wife's cognition differently, leading to a correlation confounded by unobserved household characteristics. Therefore, the regression models in panel C further adjust for the log-transformed household income and total net worth. Across all specifications in panels A-D, the obtained coefficient estimates on secondhand smoke exposure are significant at least at the 5% level with similar effect size. As is evident from the signs of the estimates, the results support our hypothesis that secondhand smoking facilitates cognitive performance of the non-smoking spouse.

In Table 3.6, the association between secondhand smoke exposure and the probability of cognitive impairment is explored. As aging-related factors would play a major role in cognitive decline, the cognition-enhancing effect of secondhand smoke exposure might be small in those with severe cognitive impairment. To identify individuals with different degrees of cognitive dysfunction, this analysis employs three cutoffs (e.g., $\mu - 1\sigma$, $\mu - 1.5\sigma$, and $\mu - 2\sigma$) as suggested in Han et al. (2008). Although a threshold of 23/24 has been used in the previous studies using the MMSE, there is no consensus on which cutoff should be used for a K-MMSE score. Given that our sample excludes certain age groups, utilizing sample characteristics may yield more appropriate cutoffs. The mean and standard deviation of the sample for household-level analysis are 26.72 and 3.60. The coefficient estimate on the husband's current smoking in column (1) is significantly different from zero at the 5% level. The next two columns find much smaller coefficient estimates which are only marginally significant or insignificant.[3] This supports our hypothesis that smoking-cognition correlation becomes weaker in the demented subjects. Notice that these estimates are only suggestive because smoking prevalence is very low among those with severe cognitive impairment, and this could attenuate our coefficient estimates.

3.4 Conclusion

This study examines the relationship between smoking and cognitive functioning by analyzing a longitudinal data from Korean population. Consistent with the previous findings on

[3]The binary indicators of cognitive impairment are estimated by a linear probability model. It has been shown that a nonlinear model with fixed effects is inconsistent in finite samples with a bias that increases the smaller the time dimension (Green, 2002).

nicotinic effects, we find consistent evidence that current smokers fare significantly better than the former smokers in terms of cognitive functioning. A relatively novel finding is the positive association of secondhand smoke exposure with cognitive functioning. Our analyses of married couples show that non-smoking spouses (or, wives) whose partner (or, husband) is currently smoking exhibit better cognition than those living with a former smoker. This relationship persists through the robustness checks that consider smoking cessation influenced by the mortality outcomes of a non-smoking spouse and unobserved family-level characteristics such as total income and net worth. Our estimates of secondhand smoke effect explain approximately 1.4%-1.7% between-survey variations in cognitive functioning. This is modest in magnitude but as large as the impact of regular exercise and employment on cognition. Further analyses suggest that the cognitive benefits of secondhand smoke will be more pronounced for normal subjects or those with mild cognitive impairment. Altogether, our results suggest that secondhand smoke may have a positive influence on preserving cognitive functioning within a 2-year time span.

We discuss several caveats that could induce bias in the estimates of passive smoking effect. First, notice that our analytic sample excludes observations represented by a proxy informant. A majority of those who could not complete the interview were cognitively incapacitated, and therefore individuals with severe cognitive impairment are under-represented in our sample. Given the evidence on the therapeutic effect of nicotine increasing with cognitive impairment, our estimates should be understood as the lower bounds of true secondhand smoke-cognition correlation. Second, our fixed effects estimator only captures the smoking effect over a 2-year period. This implies that the negative impact of smoking via cardiovascular mortality is likely to be underestimated, leading to an inflation of positive smoking effect. Third, one might argue that there are still some factors left outside the model that spuriously induces smoking-cognition correlations. More importantly, cognitive aging could promote smoking cessation, and hence this could turn into a positive association between smoking and cognition in a regression model. A more suitable approach is to isolate exogenous variation in smoking by finding an instrument that affects cognitive functioning only indirectly through the changes in smoking behaviors. Unfortunately, our data does not provide information that can be used to implement instrumental variable techniques. Thus, future work is necessary on whether smoking cessation has a positive causal effect on cognitive functioning.

Table 3.1: Sample characteristics

	Never smokers	Past smokers	Current smokers	Full sample
Cognitive functions:				
Orientation for time (0-5)	4.77	4.78	4.84	4.78
Orientation for place (0-5)	4.75	4.79	4.84	4.77
Immediate recall (0-3)	2.71	2.73	2.78	2.72
Delayed recall (0-3)	2.09	2.15	2.23	2.12
Serial 7 (0-5)	3.80	4.13	4.14	3.90
Language (0-8)	7.25	7.44	7.48	7.32
Visual construction (0-1)	0.81	0.89	0.88	0.83
Episodic memory (0-6)	4.79	4.88	5.01	4.84
K-MMSE 14 (0-14)	11.5	11.9	12.1	11.6
K-MMSE 30 (0-30)	26.2	26.9	27.2	26.5
Covariates:				
Never smoker (0,1)				0.69
Past smoker (0,1)				0.13
Current smoker (0,1)				0.18
Age (45-75)	61.1	62.8	59.6	61.1
Married (0,1)	0.82	0.92	0.86	0.84
SR health: good or better (0,1)	0.75	0.77	0.81	0.76
High blood pressure (0,1)	0.32	0.35	0.24	0.31
Diabetes (0,1)	0.13	0.19	0.15	0.14
Heart problem (0,1)	0.06	0.09	0.04	0.06
Stroke (0,1)	0.03	0.06	0.03	0.03
Psychiatric problem (0,1)	0.03	0.03	0.03	0.03
Obese (0,1)	0.03	0.02	0.02	0.03
Exercise (0,1)	0.38	0.48	0.31	0.38
Not drinking (0,1)	0.66	0.15	0.16	0.50
Employed (0,1)	0.41	0.58	0.68	0.48
Household income§ (10,000 won)	2,215	2,474	2,461	2,307
Total net worth§ (10,000 won)	10,900	14,418	10,767	11,135
Observations	20,922	3,875	5,600	30,397

Notes: Korean Longitudinal Study of Aging (KLoSA) 2006-2014. MMSE 30 (0-30) is based on orientation for time (0-5), orientation for place (0-5), immediate recall (0-3), delayed recall (0-3), serial 7 (0-5), language (0-8), and visual construction (0-1). MMSE 14 (0-14) consists of orientation for time (0-5), delayed recall (0-3), serial 7 (0-5), and visual construction (0-1). Episodic memory (0-6) is the sum of immediate recall (0-3) and delayed recall (0-3). Total net worth sums financial wealth (cash equivalents, liquid savings, bonds and bond funds, stocks, and the amount contributed to private savings club) with the net value of real estate, vehicles, businesses, and other nonfinancial assets. All currency figures are adjusted to 2014 won using South Korean Consumer Price Index distributed by Statistics Korea. Median values are reported for income and net worth and denoted by §.

Table 3.2: Impact of smoking on cognitive functioning

Response:	K-MMSE 30	K-MMSE 14	Memory
	(1)	(2)	(3)
Current smoker	0.340*	0.168	0.065
	(0.181)	(0.120)	(0.070)
Past smoker	0.088	0.008	-0.019
	(0.192)	(0.127)	(0.074)
Age	0.444***	0.333***	0.044
	(0.156)	(0.103)	(0.060)
Age squared	-0.003***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)
Married	-0.106	-0.137	-0.077
	(0.142)	(0.094)	(0.055)
SR health: fair	0.940***	0.393***	0.262***
	(0.113)	(0.075)	(0.043)
SR health: good	1.459***	0.731***	0.389***
	(0.119)	(0.079)	(0.046)
SR health: very good	1.692***	0.884***	0.515***
	(0.123)	(0.081)	(0.047)
SR health: excellent	1.422***	0.798***	0.523***
	(0.161)	(0.107)	(0.062)
High blood pressure	-0.115	-0.080	-0.043
	(0.091)	(0.060)	(0.035)
Diabetes	0.007	-0.028	-0.017
	(0.129)	(0.085)	(0.050)
Heart disease	0.020	0.013	-0.052
	(0.167)	(0.110)	(0.064)
Stroke	-1.447***	-0.745***	-0.259***
	(0.216)	(0.143)	(0.083)
Psychiatric problem	-0.799***	-0.533***	-0.127
	(0.246)	(0.162)	(0.094)
Obese	-0.667***	-0.462***	-0.135***
	(0.129)	(0.085)	(0.049)
Exercise	0.178***	0.073**	0.062***
	(0.045)	(0.030)	(0.017)
Not drinking	-0.160	-0.022	0.045
	(0.151)	(0.100)	(0.058)
Employed	0.239***	0.120***	0.041*
	(0.059)	(0.039)	(0.022)
Observations	30,397	30,397	30,397
Persons	7,296	7,296	7,296
Rho	0.71	0.78	0.49
Hausman test (χ^2 value)	640.4	698.4	342.9

Notes: Robust standard errors in parentheses are clustered at the individual level. 'Rho' is the variance share of unobserved heterogeneity. Hausman test evaluates the null hypothesis that the differences in coefficients of fixed and random effects model are not systematic. Significance levels are indicated by *, **, and *** for 10, 5, and 1 percent level, respectively.

Table 3.3: Impact of smoking on cognitive functioning: Ever smokers

Response:	K-MMSE 30	K-MMSE 14	Memory
	(1)	(2)	(3)
Panel A: OLS estimate on current smoking			
Current smoker	0.219**	0.132*	0.078*
	(0.103)	(0.069)	(0.041)
Observations	9,475	9,475	9,475
Persons	2,363	2,363	2,363
Panel B: Moderation analysis			
Current smoker	0.227*	0.191**	0.034
	(0.127)	(0.085)	(0.050)
Vascular disease	-0.224	0.041	-0.176**
	(0.181)	(0.120)	(0.071)
Current smoker ×	0.052	-0.107	0.129*
Vascular disease	(0.180)	(0.120)	(0.071)
Observations	9,475	9,475	9,475
Persons	2,363	2,363	2,363
Panel C: OLS estimate on smoking intensity			
Moderate smoker	0.214*	0.159*	0.084
	(0.129)	(0.087)	(0.052)
Heavy smoker	-0.041	-0.004	-0.041
	(0.152)	(0.102)	(0.061)
Very heavy smoker	-0.087	-0.030	-0.007
	(0.173)	(0.116)	(0.070)
Observations	5,742	5,742	5,742
Persons	2,111	2,111	2,111

Notes: The sample is reduced to former or current smokers. Robust standard errors in parentheses are clustered at the individual level. Regression models control for a full set of covariates including individual characteristics, year fixed effects, province dummies, and a learning effect indicator. Vascular disease includes high blood pressure, diabetes, heart disease, and stroke. Smoking intensity in panel C is defined as light (pack-year deciles 1-3), medium (pack-year deciles 4-6), heavy (pack-year deciles 7-8), and very heavy (pack-year deciles 9-10). Significance levels are indicated by *, **, and *** for 10, 5, and 1 percent level, respectively.

Table 3.4: Impact of secondhand smoke on cognitive functioning: Ever smokers

Response:	K-MMSE 30 of wife (1)	K-MMSE 30 of wife (2)	K-MMSE 30 of nonsmoker (3)
Current smoker: husband	0.348***	0.357***	
	(0.132)	(0.134)	
Any spouse currently smoking			0.401***
			(0.133)
Current smoker: wife	0.836		
	(0.587)		
Observations	6,443	6,314	6,359
Households	1,600	1,583	1,591
Rho	0.64	0.64	0.76
Hausman test (χ^2 value)	146.4	143.8	147.1

Notes: The sample excludes the households where both spouses are never smokers. This sample selection is equivalent to the analyses in Table 3. Robust standard errors in parentheses are clustered at the household level. Column (2) further reduces to the households where the wife is currently not smoking. Column (3) excludes the households where both spouses are currently smoking. All regression models include individual characteristics measured separately for husband and wife, year fixed effects, province dummies, and a learning effect indicator. Significance levels are indicated by *, **, and *** for 10, 5, and 1 percent level, respectively.

Table 3.5: Robustness checks

Response:	K-MMSE 30 of wife (1)	K-MMSE 30 of wife (2)	K-MMSE 30 of nonsmoker (3)
Panel A: Excludes HHs where the husband quit smoking when the wife reported poor/fair health			
Current smoker: husband	0.292**	0.296**	
	(0.136)	(0.137)	
Any spouse currently smoking			0.340**
			(0.137)
Current smoker: wife	0.957		
	(0.636)		
Observations	5,924	5,812	5,850
Households	1,473	1,458	1,464
Panel B: Excludes HHs where the husband quit smoking when the wife is diagnosed with vascular disease			
Current smoker: husband	0.334**	0.344**	
	(0.137)	(0.139)	
Any spouse currently smoking			0.386***
			(0.138)
Current smoker: wife	0.698		
	(0.596)		
Observations	6,190	6,063	6,106
Households	1,542	1,525	1,533
Panel C: Controlling for log-transformed household income and total net worth			
Current smoker: husband	0.350***	0.359***	
	(0.132)	(0.134)	
Any spouse currently smoking			0.403***
			(0.133)
Current smoker: wife	0.865		
	(0.590)		
Log(HH income)	0.045	0.049	0.043
	(0.031)	(0.032)	(0.032)
Log(Total net worth)	0.022**	0.020*	0.019*
	(0.011)	(0.011)	(0.011)
Observations	6,443	6,314	6,359
Households	1,600	1,583	1,591

Notes: The sample excludes the households where both spouses are never smokers. Robust standard errors in parentheses are clustered at the household level. Column (2) further reduces to the households where the wife is currently not smoking. Column (3) excludes the households where both spouses are currently smoking. Vascular disease indicators for panel C includes high blood pressure, diabetes, heart disease, and stroke. Significance levels are indicated by *, **, and *** for 10, 5, and 1 percent level, respectively.

Table 3.6: Impact of secondhand smoke on cognitive impairment: Ever smokers

Response:	Binary variable for cognitive impairment		
Cutoff:	Wife's K-MMSE $30 \leq \mu - 1\sigma$	Wife's K-MMSE $30 \leq \mu - 1.5\sigma$	Wife's K-MMSE $30 \leq \mu - 2\sigma$
	(1)	(2)	(3)
Current smoker: husband	-0.038**	-0.023*	-0.009
	(0.015)	(0.013)	(0.010)
Observations	6,314	6,314	6,314
Households	1,583	1,583	1,583

Notes: The sample is reduced to the households where both spouses are never smokers and the wife is currently not smoking. This sample selection is equivalent to column (2) of Tables 4. The models are estimated by OLS with fixed effects. Robust standard errors in parentheses are clustered at the household level. The mean and standard deviation in this sample are 26.72 and 3.60. All regression models include individual characteristics measured separately for husband and wife, year fixed effects, province dummies, and a learning effect indicator. Significance levels are indicated by *, **, and *** for 10, 5, and 1 percent level, respectively.

3.5 References

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Chapter 4

Summary and Conclusions

This thesis has examined the impact of the institutional factor (basic pension) and risky health behavior on the well-being outcomes among the South Korean elderly population. Essay I found that the expansion of the basic pension in 2014 increased financial satisfaction but had no impact on other domains of subjective well-being. Our estimates of policy effect were nearly twice as high as the previous estimates that used the introduction of policy in 2008 as a natural experiment. This comparison indicates that the basic pension has been indeed effective in reducing poverty and improving quality of life. Essay II explored how smoking cessation affects the partner's cognitive functioning among married couples. The results confirm the hypothesis that smoking has a protective effect on cognition. Our study is based on the nationally representative sample of Korean population above age 45, meaning that the neuroprotective impact of smoking might be generalizable to the population level. However, these findings should be interpreted with caution as the adverse impact of smoking would exceed the gains from nicotinic stimulation in the long-run. Since our study uses a biannual survey and variation comes from smoking cessation within a two-year time span, our estimates capture only the short-term effect of smoking cessation on cognition.

It is important to note that our estimates in both essays do not necessarily capture the causal effects. In Essay II, the causal effect of smoking can only be captured with the instrumental variable that affects cognition only indirectly through changes in smoking behaviors. The future research may exploit the 2016 cigarette price increase in South Korea as the source of exogenous variation. Since only smokers are affected by cigarette price increase and the policy change was not motivated by public health concerns, this strategy will allow the researchers to isolate the causal effect of smoking. In Essay I, the empirical strategy rests on a set of strong assumptions that are required for "matching on observables." For example, the non-treated individuals with similar characteristics as the treated group are assumed to resemble the behaviors of the treated persons when they were untreated. However, there is no way to confirm how plausible this assumption is and how to control for differences in unobserved characteristics. As in Essay I, a more suitable approach is to isolate causal effect using an exogenous variation. The future study may want to use an alternative dataset that includes information on the potential endogenous regressor.

Chapter 5

Appendix

5.1 Algorithm for Nearest Neighbor Matching

Nearest neighbor (NN) matching selects untreated subjects whose propensity score is closest to that of the treated subject. If i and j represent the treated and untreated subject, a set of untreated subjects matched to treated subjects i is chosen such that,

$$C(p_i) = \min_j |p_i - p_j| \tag{5.1}$$

NN matching can be implemented with a pre-specified caliper to avoid bad matches in which the closest match is in distance. That is, a match for subject i is selected only if $\delta > |p_i - p_j|$, where δ is the maximum distance allowed. The smaller the size of δ, the better the quality of the matches. If none of the untreated subjects is within a tolerance level from the treated subject i, these treated subjects are excluded from the analysis to impose a common support condition. For k-to-1 NN matching, k controls with closest propensity scores are matched with each treated subject. Using more than one match leads to a larger bias but reduces variance by using more information to construct the counterfactual group.

The estimation can be implemented either with replacement or without replacement. When matching is performed with replacement, the same comparison group observation can be used repeatedly as a match. In the matching without replacement, a comparison individual can be matched only once. Dehejia and Wahba (2002) showed that NN matching without replacement would match the treated with controls with very different propensity scores and results in bad matches. It also has a drawback that the final estimate without replacement depends on the initial ordering of the treated observations for which the matches were selected (Smith and Todd, 2005). In general, it is advised to allow replacement (Caliendo and Kopeinig, 2008).

5.2 Algorithm for Kernel Matching

Kernel matching matches treated subjects with a weighted average of all controls where weights are inversely proportional to the distance between the treated and control group's propensity scores. Because all control units contribute to the weights, variance is smaller than other matching estimators. The Kernel matching estimator is given by

$$\tau^{Kernel} = \frac{1}{N_{D_1}} \sum_{i \in D_1} \left[Y_{i1} - \frac{\sum_{j \in D_0} Y_{j0} G\left(\frac{p_j - p_i}{h}\right)}{\sum_{k \in D_0} G\left(\frac{p_k - p_i}{h}\right)} \right] \tag{5.2}$$

where $G(\cdot)$ is a Kernel function and h is a bandwidth parameter (Becker and Ichino, 2002). The second term within a bracket, $\frac{\sum_{j \in D_0} Y_{j0} G\left(\frac{p_j - p_i}{h}\right)}{\sum_{k \in D_0} G\left(\frac{p_k - p_i}{h}\right)}$, is a consistent estimator of the counterfactual outcome $E(Y_{i0}|D_i = 1)$. Of particular importance in Kernel matching is the choice of h. High bandwidth values reduce variance between the estimated and underlying density function while inducing bias in the estimated density. Small bandwidth exacerbates the problem of common support and increase variance but improve matching quality by reducing bias (Caliendo and Kopeinig, 2008).

5.3 Essay I: Computer Codes

```
********************
***** Input.do *****
********************

clear all
set more off
set maxvar 25000

use D:\Research\boap_qol\Data\w01_main_k.dta, clear
merge 1:1 pid using "D:\Research\boap_qol\Data\w02_main_k.dta"
drop _merge
merge 1:1 pid using "D:\Research\boap_qol\Data\w03_main_k.dta"
drop _merge
merge 1:1 pid using "D:\Research\boap_qol\Data\w04_main_k.dta"
```

```
drop _merge
merge 1:1 pid using "D:\Research\boap_qol\Data\w05_main_k.dta"
drop _merge

#delimit;

/*
*****************************************************;
***** Discount factors (CPI All Urban Consumers) *****;
*****************************************************;
Year Annual average
2005 86.1
2006 88.1
2007 90.2
2008 94.5
2009 97.1
2010 100.0
2011 104.0
2012 106.3
2013 107.7
2014 109.0
*/
local discf1 1.23723;
local discf2 1.15344;
local discf3 1.09;
local discf4 1.0254;
local discf5 1;


*** Sampling weight ***;
gen wgta1=.;
forv i=2/4 {;
gen wgta`i'=w0`i'wgt01;
};
gen wgta5=w05wgt_p;

gen wgtb1=.;
forv i=2/4 {;
gen wgtb`i'=w0`i'wgt02;
};
gen wgtb5=w05wgt_c;


*** Interview date ***;
forv i=1/5 {;
gen intyr`i'=w0`i'mniw_y;
gen intmo`i'=w0`i'mniw_m;
};


*********************************;
***** DEMOGRAPHIC VARIABLES *****;
*********************************;

*** Age ***;
gen age1=w01a001_age;
forv i=2/5 {;
gen age`i'=w0`i'a002_age;
};
gen byr1=2006-age1;
gen byr2=2008-age2;
gen byr3=2010-age3;
gen byr4=2012-age4;
gen byr5=2014-age5;

forv i=1/5 {;
gen age_sq`i'=age`i'*age`i';
};
```

```
forv i=1/5 {;
gen cohort`i'=.;
replace cohort`i'=1 if (byr`i'>=1910 & byr`i'<=1920);
replace cohort`i'=2 if (byr`i'>=1921 & byr`i'<=1930);
replace cohort`i'=3 if (byr`i'>=1931 & byr`i'<=1940);
replace cohort`i'=4 if (byr`i'>=1941 & byr`i'<=1950);
replace cohort`i'=5 if (byr`i'>=1951 & byr`i'<=1960);
replace cohort`i'=6 if (byr`i'>=1961 & byr`i'<=1970);
};


*** Gender ***;
forv i=1/5 {;
gen female`i'=(w0`i'gender1==5);
};

*** Education ***;
forv i=1/5 {;
gen lesshigh`i'=(w0`i'edu==1);
gen middle`i'=(w0`i'edu==2);
gen high`i'=(w0`i'edu==3 | w0`i'edu==4);
};
forv i=1/5 {;
gen educ`i'=w0`i'edu;
replace educ`i'=. if (educ`i'==-8 | educ`i'==-9);
};

*** Marital ***;
gen marr1=(w01a006==1);
forv i=2/5 {;
gen marr`i'=(w0`i'marital==1);
};

*** Region dummies ***;
forv i=1/5 {;
gen state`i'=w0`i'region1;
gen county`i'=w0`i'region2;
gen city`i'=(w0`i'region3==1);
gen rform`i'=w0`i'enu_type;
};

*** Number of live children ***;
gen nochld1=w01ba01;
forv i=2/5 {;
gen nochld`i'=w0`i'ba003;
};
forv i=1/5 {;
replace nochld`i'=. if (nochld`i'==-8 |  nochld`i'==-9);
*replace nochld`i'=0 if (nochld`i'==.);

*replace nochld`i'=nochld`i'+1 if (marr`i'==0);
*replace nochld`i'=nochld`i'+2 if (marr`i'==1);
};


***************************;
***** Health variable *****;
***************************;

*** SR health ***;
forv i=1/5 {;
gen srhlth`i'=w0`i'c001;
replace srhlth`i'=. if (srhlth`i'==-8);
replace srhlth`i'=6-srhlth`i';

gen shgood`i'=(srhlth`i'==3 | srhlth`i'==4 | srhlth`i'==5);
```

```
};

*** Disability ***;
gen disab1=(w01c002==1);
forv i=2/5 {;
gen disab`i'=(w0`i'c003==1);
};


*** CES-D10 ***;
gen cesd1=w01dep2;
replace cesd1=cesd1*10;
forv i=2/4 {;
gen cesd`i'=w0`i'sumcesd;
};
gen cesd5=w05sumcesd;


*** ADL & IADL ***;
forv i=1/5 {;
gen adl`i'=w0`i'adl;
gen iadl`i'=w0`i'iadl;
};

*** Cognitive score ***;
forv i=1/5 {;
gen cog`i'=w0`i'mmse;
gen dem`i'=(w0`i'mmseg==1);
};
gen proxy1=(w01ce50==5);
forv i=2/5 {;
gen proxy`i'=(w0`i'c550==5);
};
gen regis1=w01cd06;
forv i=2/5 {;
gen regis`i'=w0`i'c406;
};

*** Grip strength ***;
forv i=1/5 {;
gen grip`i'=w0`i'mgrip;
replace grip`i'=. if (w0`i'mgrip==-8);
};

*** Smoking, drinking, exercise ***;
gen exrc1=(w01c096==1);
forv i=2/4 {;
gen exrc`i'=(w0`i'c108==1);
};
gen exrc5=(w05c116==1);

forv i=1/5 {;
gen smok_p`i'=(w0`i'smoke==1);
gen smok_c`i'=(w0`i'smoke==2);

gen drnk_p`i'=(w0`i'alc==1);
gen drnk_c`i'=(w0`i'alc==2);
};


*** Health state satisfaction ***;
forv i=1/4 {;
gen hlthsat`i'=w0`i'g025;
gen econsat`i'=w0`i'g026;
gen marrsat`i'=w0`i'g027;
gen chilsat`i'=w0`i'g028;
gen lifesat`i'=w0`i'g029;
};
```

```
gen hlthsat5=w05g026;
gen econsat5=w05g027;
gen marrsat5=w05g028;
gen chilsat5=w05g029;
gen lifesat5=w05g030;

forv i=1/5 {;
replace hlthsat`i'=. if (hlthsat`i'==-8 | hlthsat`i'==-9);
replace econsat`i'=. if (econsat`i'==-8 | econsat`i'==-9);
replace marrsat`i'=. if (marrsat`i'==-8 | marrsat`i'==-9);
replace chilsat`i'=. if (chilsat`i'==-8 | chilsat`i'==-9);
replace lifesat`i'=. if (lifesat`i'==-8 | lifesat`i'==-9);
};


********************************************;
***** Health care access and insurance *****;
********************************************;

*** Public health insurance ***;
gen pbhi1=(w01cc01==1);
forv i=2/5 {;
gen pbhi`i'=(w0`i'c301==1);
};

*** Private health insurance ***;
gen pvhi1=(w01cc10==1);
forv i=2/5 {;
gen pvhi`i'=(w0`i'c310==1);
};


*** Doctor visits ***;
replace w01cc30=. if (w01cc30==-8 | w01cc30==-9);
forv i=2/4 {;
replace w0`i'c334=. if (w0`i'c334==-8 | w0`i'c334==-9);
};
replace w05c352=. if (w05c352==-8 | w05c352==-9);

replace w01cc32=. if (w01cc32==-8 | w01cc32==-9);
forv i=2/4 {;
replace w0`i'c337=. if (w0`i'c337==-8 | w0`i'c337==-9);
};
replace w05c355=. if (w05c355==-8 | w05c355==-9);

replace w01cc34=. if (w01cc34==-8 | w01cc34==-9);
forv i=2/4 {;
replace w0`i'c340=. if (w0`i'c340==-8 | w0`i'c340==-9);
};
replace w05c358=. if (w05c358==-8 | w05c358==-9);


egen docvis1=rowtotal(w01cc30 w01cc32 w01cc34);
forv i=2/4 {;
egen docvis`i'=rowtotal(w0`i'c334 w0`i'c337 w0`i'c340);
};
egen docvis5=rowtotal(w05c352 w05c355 w05c358);


*** Prescription drug access ***;
replace w01cc36=. if (w01cc36==-8 | w01cc36==-9);
forv i=2/4 {;
replace w0`i'c343=. if (w0`i'c343==-8 | w0`i'c343==-9);
};
replace w05c361=. if (w05c361==-8 | w05c361==-9);

gen presc1=(w01cc36==1);
forv i=2/4 {;
```

```
gen presc`i'=(w0`i'c343==1);
};
gen presc5=(w05c361==1);


*********************;
***** Employment *****;
*********************;

*** Retirement status ***;
forv i=1/5 {;
gen work`i'=(w0`i'd001==1);
gen empl`i'=(w0`i'ecoact==1);

gen ret`i'=(w0`i'd001==5);
};


*****************************;
******* Income and Asset *****;
*****************************;

*** Labor income ***;
forv i=1/5 {;
gen linc`i'=w0`i'e003;
replace linc`i'=. if (w0`i'e003==-8 | w0`i'e003==-9);
};

*** Total HH income ***;
forv i=1/4 {;
gen hhinc`i'=w0`i'e126;
replace hhinc`i'=. if (w0`i'e126==-8 | w0`i'e126==-9);
};
gen hhinc5=w05e147;
replace hhinc5=. if (w05e147==-8 | w05e147==-9);

*forv i=1/5 {;
* replace hhinc`i'=log(hhinc`i'+.01);
*};

*** Total HH wealth ***;
forv i=1/4 {;
*** Asset ***;
replace w0`i'f005=. if (w0`i'f005==-8 | w0`i'f005==-9);
replace w0`i'f031=. if (w0`i'f031==-8 | w0`i'f031==-9);
replace w0`i'f037=. if (w0`i'f037==-8 | w0`i'f037==-9);
replace w0`i'f050=. if (w0`i'f050==-8 | w0`i'f050==-9);
replace w0`i'f078=. if (w0`i'f078==-8 | w0`i'f078==-9);
replace w0`i'f085=. if (w0`i'f085==-8 | w0`i'f085==-9);
replace w0`i'f092=. if (w0`i'f092==-8 | w0`i'f092==-9);
replace w0`i'f099=. if (w0`i'f099==-8 | w0`i'f099==-9);
replace w0`i'f106=. if (w0`i'f106==-8 | w0`i'f106==-9);
replace w0`i'f139=. if (w0`i'f139==-8 | w0`i'f139==-9);
replace w0`i'f146=. if (w0`i'f146==-8 | w0`i'f146==-9);
replace w0`i'f173=. if (w0`i'f173==-8 | w0`i'f173==-9);
replace w0`i'f180=. if (w0`i'f180==-8 | w0`i'f180==-9);

*** Debt ***;
replace w0`i'f198=. if (w0`i'f198==-8 | w0`i'f198==-9);
replace w0`i'f198=(w0`i'f198*-1);
replace w0`i'f205=. if (w0`i'f205==-8 | w0`i'f205==-9);
replace w0`i'f205=(w0`i'f205*-1);
replace w0`i'f212=. if (w0`i'f212==-8 | w0`i'f212==-9);
replace w0`i'f212=(w0`i'f212*-1);
replace w0`i'f220=. if (w0`i'f220==-8 | w0`i'f220==-9);
replace w0`i'f220=(w0`i'f220*-1);
};
```

```
forv i=1/4 {;
*** Total financial wealth ***;
egen totfw`i'=rowtotal(w0`i'f085 w0`i'f092 w0`i'f099 w0`i'f106 w0`i'f139 w0`i'f146);
*replace totfw`i'=. if (w0`i'f085==. & w0`i'f092==. & w0`i'f099==. & w0`i'f106==. & w0`i'f139==. & w0`i'f146==.);
*gen totfw`i'=w0`i'f085 + w0`i'f092 + w0`i'f099 + w0`i'f106 + w0`i'f139 + w0`i'f146;
*** Total wealth ***;
egen totnwa`i'=rowtotal(w0`i'f005 w0`i'f031 w0`i'f037 w0`i'f050 w0`i'f078 w0`i'f085 w0`i'f092 w0`i'f099 w0`i'f106
w0`i'f139 w0`i'f146 w0`i'f173 w0`i'f180 w0`i'f198 w0`i'f205 w0`i'f212 w0`i'f220);
*replace totnwa`i'=. if (w0`i'f005==. & w0`i'f031==. & w0`i'f037==. & w0`i'f050==. & w0`i'f078==. & w0`i'f085==.
& w0`i'f092==. & w0`i'f099==. & w0`i'f106==. & w0`i'f139==. & w0`i'f146==. & w0`i'f173==. & w0`i'f180==. & w0`i'f198==.
& w0`i'f205==. & w0`i'f212==. & w0`i'f220==.);
*gen totnwa`i'=w0`i'f005 + w0`i'f031 + w0`i'f037 + w0`i'f050 + w0`i'f078 + w0`i'f085 + w0`i'f092 + w0`i'f099 +
w0`i'f106 + w0`i'f139 + w0`i'f146 + w0`i'f173 + w0`i'f180 + w0`i'f198 + w0`i'f205 + w0`i'f212 + w0`i'f220;
};

*** Asset ***;
replace w05f007=. if (w05f007==-8 | w05f007==-9);
replace w05f035=. if (w05f035==-8 | w05f035==-9);
replace w05f043=. if (w05f043==-8 | w05f043==-9);
replace w05f058=. if (w05f058==-8 | w05f058==-9);
replace w05f086=. if (w05f086==-8 | w05f086==-9);
replace w05f095=. if (w05f095==-8 | w05f095==-9);
replace w05f102=. if (w05f102==-8 | w05f102==-9);
replace w05f109=. if (w05f109==-8 | w05f109==-9);
replace w05f116=. if (w05f116==-8 | w05f116==-9);
replace w05f139=. if (w05f139==-8 | w05f139==-9);
replace w05f146=. if (w05f146==-8 | w05f146==-9);
replace w05f175=. if (w05f175==-8 | w05f175==-9);
replace w05f182=. if (w05f182==-8 | w05f182==-9);

*** Debt ***;
replace w05f206=. if (w05f206==-8 | w05f206==-9);
replace w05f206=(w05f206*-1);
replace w05f213=. if (w05f213==-8 | w05f213==-9);
replace w05f213=(w05f213*-1);
replace w05f220=. if (w05f220==-8 | w05f220==-9);
replace w05f220=(w05f220*-1);
replace w05f228=. if (w05f228==-8 | w05f228==-9);
replace w05f228=(w05f228*-1);

*** Total financial wealth ***;
egen totfw5=rowtotal(w05f095 w05f102 w05f109 w05f116 w05f139 w05f146);
replace totfw5=. if (w05f095==. & w05f102==. & w05f109==. & w05f116==. & w05f139==. & w05f146==.);
*** Total wealth ***;
egen totnwa5=rowtotal(w05f007 w05f035 w05f043 w05f058 w05f086 w05f095 w05f102 w05f109 w05f116 w05f139 w05f146
w05f175 w05f182 w05f206 w05f213 w05f220 w05f228);
replace totnwa5=. if (w05f007==. & w05f035==. & w05f043==. & w05f058==. & w05f086==. & w05f095==. & w05f102==.
& w05f109==. & w05f116==. & w05f139==. & w05f146==. & w05f175==. & w05f182==. & w05f206==. & w05f213==. & w05f220==.
& w05f228==.);


forv i=1/5 {;
replace linc`i'=linc`i'*`discf`i'';
replace hhinc`i'=hhinc`i'*`discf`i'';
replace totnwa`i'=totnwa`i'*`discf`i'';
replace totfw`i'=totfw`i'*`discf`i'';
};

forv i=1/5 {;
gen linc_sq`i'=linc`i'*linc`i';
gen hhinc_sq`i'=hhinc`i'*hhinc`i';
gen totnwa_sq`i'=totnwa`i'*totnwa`i';
gen totfw_sq`i'=totfw`i'*totfw`i';
};

*** Home & RA ownership ***;
forv i=1/5 {;
gen hown`i'=(w0`i'f001==1);
```

```
};
forv i=1/4 {;
gen real`i'=(w0`i'f049==1);
};
gen real5=(w05f057==1);


*************************;
***** Pension income *****;
*************************;

*** National pension plan ***;
forv i=1/5 {;
gen npp`i'=(w0`i'e033==1 | w0`i'e033==2 | w0`i'e033==3);
};

forv i=1/5 {;
replace w0`i'e035=. if (w0`i'e035==-8 | w0`i'e035==-9);
*replace w0`i'e036=. if (w0`i'e036==-8 | w0`i'e036==-9);

gen a_npp`i'=w0`i'e035;
replace a_npp`i'=0 if (a_npp`i'==.);
replace a_npp`i'=a_npp`i'*`discf`i'';
};


*** Social welfare benefits ***;
forv i=1/5 {;
gen w05e070m0`i'=w05e070m`i';
};

forv i=1/5 {;
gen swb`i'=(w0`i'e070m01==1 | w0`i'e070m02==1 | w0`i'e070m03==1 | w0`i'e070m04==1 | w0`i'e070m05==1);
*gen swb`i'=(w0`i'e070m03==1 | w0`i'e070m05==1);

egen a_swb`i'=rowtotal(w0`i'e073 w0`i'e083 w0`i'e092 w0`i'e102 w0`i'e112);
replace a_swb`i'=a_swb`i'*`discf`i'';
};


*** Basic old-age pension ***;
forv i=2/4 {;
replace w0`i'g110=. if (w0`i'g110==-8 | w0`i'g110==-9);
};
replace w05g112=. if (w05g112==-8 | w05g112==-9);


gen boap1=0;
forv i=2/4 {;
gen boap`i'=(w0`i'g110!=.);
};
gen boap5=(w05g112!=.);


gen a_boap1=0;
forv i=2/4 {;
gen a_boap`i'=w0`i'g110;
};
gen a_boap5=w05g112;


save "D:\Research\boap_qol\Data\klosa_wide.dta", replace;



****************************
```

```
***** cleaning_wide.do *****
***************************

#delimit;

gen did_cog = cog5 - cog4;
gen did_cesd = cesd5 - cesd4;
gen did_srhlth = srhlth5 - srhlth4;
gen did_grip = grip5 - grip4;

gen did_hlthsat = hlthsat5 - hlthsat4;
gen did_econsat = econsat5 - econsat4;
gen did_marrsat = marrsat5 - marrsat4;
gen did_chilsat = chilsat5 - chilsat4;
gen did_lifesat = lifesat5 - lifesat4;


foreach v in econsat4 econsat5 did_econsat hlthsat4 hlthsat5 did_hlthsat lifesat4 lifesat5 did_lifesat age4
age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4 {;
drop if missing(`v');
};


gen age_elig=(age5>=65 & age5!=.);
keep if age_elig==1;

gen treat=0;
replace treat=1 if ((age_elig==1) & (boap4==1));
replace treat=1 if ((age_elig==1) & (boap4==0 & boap5==1));




**********************************
***** cleaning_wide_wave34.do *****
**********************************
#delimit;

gen did_cog = cog4 - cog3;
gen did_cesd = cesd4 - cesd3;
gen did_srhlth = srhlth4 - srhlth3;
gen did_grip = grip4 - grip3;

gen did_hlthsat = hlthsat4 - hlthsat3;
gen did_econsat = econsat4 - econsat3;
gen did_marrsat = marrsat4 - marrsat3;
gen did_chilsat = chilsat4 - chilsat3;
gen did_lifesat = lifesat4 - lifesat3;

foreach v in econsat3 econsat4 did_econsat hlthsat3 hlthsat4 did_hlthsat lifesat3 lifesat4 did_lifesat age3
age_sq3 female3 middle3 high3 marr3 ret3 hhinc3 hown3 pbhi3 pvhi3 shgood3 adl3 city3 {;
drop if missing(`v');
};

gen age_elig=(age5>=65 & age5!=.);
keep if age_elig==1;

gen treat=0;
replace treat=1 if ((age_elig==1) & (boap4==1));
replace treat=1 if ((age_elig==1) & (boap4==0 & boap5==1));



**********************************
***** cleaning_wide_wave35.do *****
**********************************
```

```
#delimit;

gen did_cog = cog5 - cog3;
gen did_cesd = cesd5 - cesd3;
gen did_srhlth = srhlth5 - srhlth3;
gen did_grip = grip5 - grip3;

gen did_hlthsat = hlthsat5 - hlthsat3;
gen did_econsat = econsat5 - econsat3;
gen did_marrsat = marrsat5 - marrsat3;
gen did_chilsat = chilsat5 - chilsat3;
gen did_lifesat = lifesat5 - lifesat3;

foreach v in econsat3 econsat5 did_econsat hlthsat3 hlthsat5 did_hlthsat lifesat3 lifesat5 did_lifesat age3
age_sq3 female3 middle3 high3 marr3 ret3 hhinc3 hown3 pbhi3 pvhi3 shgood3 adl3 city3 {;
drop if missing(‘v’);
};

gen age_elig=(age5>=65 & age5!=.);
keep if age_elig==1;

gen treat=0;
replace treat=1 if ((age_elig==1) & (boap4==1));
replace treat=1 if ((age_elig==1) & (boap4==0 & boap5==1));



***********************
***** analysis.do *****
***********************

***********************
***** Table 1 & 3 *****
***********************
use "C:\Research\boap_qol\Data\klosa_wide.dta", clear
do "C:\Research\boap_qol\Data\cleaning_wide.do"

psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4,
outcome(econsat4 econsat5 did_econsat) kernel kerneltype(normal) bw(0.01) common ate
pstest age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4, both

psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4,
outcome(chilsat4 chilsat5 did_chilsat) kernel kerneltype(normal) bw(0.01) common ate
pstest age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4, both


*pstest age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4, both graph

*keep if (_support==1)
*psgraph, treated(treat) pscore(_pscore) bin(50)


*******************
***** Table 2 *****
*******************
psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4,
outcome(econsat4 econsat5 did_econsat) kernel kerneltype(normal) bw(0.01) common ate
pstest age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4, both
psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4,
outcome(econsat4 econsat5 did_econsat) kernel kerneltype(normal) bw(0.005) common ate
pstest age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4, both
psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4,
outcome(econsat4 econsat5 did_econsat) neighbor(2) caliper(.01) common ate
pstest age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4, both
psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4,
outcome(econsat4 econsat5 did_econsat) neighbor(5) caliper(.01) common ate
pstest age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4, both
```

```
psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4,
outcome(chilsat4 chilsat5 did_chilsat) kernel kerneltype(normal) bw(0.01) common ate
pstest age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4, both
psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4,
outcome(chilsat4 chilsat5 did_chilsat) kernel kerneltype(normal) bw(0.005) common ate
pstest age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4, both
psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4,
outcome(chilsat4 chilsat5 did_chilsat) neighbor(2) caliper(.01) common ate
pstest age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4, both
psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4,
outcome(chilsat4 chilsat5 did_chilsat) neighbor(5) caliper(.01) common ate
pstest age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4, both


*******************
***** Table 4 *****
*******************
psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4,
outcome(econsat4 econsat5 did_econsat) kernel kerneltype(normal) bw(0.01) common ate
bootstrap r(att), reps(50): psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4
pvhi4 shgood4 adl4 city4, outcome(econsat4 econsat5 did_econsat) kernel kerneltype(normal) bw(0.01) common ate

psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4,
outcome(econsat4 econsat5 did_econsat) kernel kerneltype(normal) bw(0.005) common ate
bootstrap r(att), reps(50): psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4
pvhi4 shgood4 adl4 city4, outcome(econsat4 econsat5 did_econsat) kernel kerneltype(normal) bw(0.005) common
ate

psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4,
outcome(econsat4 econsat5 did_econsat) neighbor(2) caliper(.01) common ate
bootstrap r(att), reps(50): psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4
pvhi4 shgood4 adl4 city4, outcome(econsat4 econsat5 did_econsat) neighbor(2) caliper(.01) common ate

psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4,
outcome(econsat4 econsat5 did_econsat) neighbor(5) caliper(.01) common ate
bootstrap r(att), reps(50): psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4
pvhi4 shgood4 adl4 city4, outcome(econsat4 econsat5 did_econsat) neighbor(5) caliper(.01) common ate


psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4,
outcome(hlthsat4 hlthsat5 did_hlthsat) kernel kerneltype(normal) bw(0.01) common ate
bootstrap r(att), reps(50): psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4
pvhi4 shgood4 adl4 city4, outcome(hlthsat4 hlthsat5 did_hlthsat) kernel kerneltype(normal) bw(0.01) common ate

psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4,
outcome(hlthsat4 hlthsat5 did_hlthsat) kernel kerneltype(normal) bw(0.005) common ate
bootstrap r(att), reps(50): psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4
pvhi4 shgood4 adl4 city4, outcome(hlthsat4 hlthsat5 did_hlthsat) kernel kerneltype(normal) bw(0.005) common
ate

psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4,
outcome(hlthsat4 hlthsat5 did_hlthsat) neighbor(2) caliper(.01) common ate
bootstrap r(att), reps(50): psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4
pvhi4 shgood4 adl4 city4, outcome(hlthsat4 hlthsat5 did_hlthsat) neighbor(2) caliper(.01) common ate

psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4,
outcome(hlthsat4 hlthsat5 did_hlthsat) neighbor(5) caliper(.01) common ate
bootstrap r(att), reps(50): psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4
pvhi4 shgood4 adl4 city4, outcome(hlthsat4 hlthsat5 did_hlthsat) neighbor(5) caliper(.01) common ate


psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4,
outcome(chilsat4 chilsat5 did_chilsat) kernel kerneltype(normal) bw(0.01) common ate
bootstrap r(att), reps(50): psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4
pvhi4 shgood4 adl4 city4, outcome(chilsat4 chilsat5 did_chilsat) kernel kerneltype(normal) bw(0.01) common ate

psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4,
outcome(chilsat4 chilsat5 did_chilsat) kernel kerneltype(normal) bw(0.005) common ate
```

```
bootstrap r(att), reps(50): psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4
pvhi4 shgood4 adl4 city4, outcome(chilsat4 chilsat5 did_chilsat) kernel kerneltype(normal) bw(0.005) common
ate

psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4,
outcome(chilsat4 chilsat5 did_chilsat) neighbor(2) caliper(.01) common ate
bootstrap r(att), reps(50): psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4
pvhi4 shgood4 adl4 city4, outcome(chilsat4 chilsat5 did_chilsat) neighbor(2) caliper(.01) common ate

psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4,
outcome(chilsat4 chilsat5 did_chilsat) neighbor(5) caliper(.01) common ate
bootstrap r(att), reps(50): psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4
pvhi4 shgood4 adl4 city4, outcome(chilsat4 chilsat5 did_chilsat) neighbor(5) caliper(.01) common ate


psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4,
outcome(lifesat4 lifesat5 did_lifesat) kernel kerneltype(normal) bw(0.01) common ate
bootstrap r(att), reps(50): psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4
pvhi4 shgood4 adl4 city4, outcome(lifesat4 lifesat5 did_lifesat) kernel kerneltype(normal) bw(0.01) common ate

psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4,
outcome(lifesat4 lifesat5 did_lifesat) kernel kerneltype(normal) bw(0.005) common ate
bootstrap r(att), reps(50): psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4
pvhi4 shgood4 adl4 city4, outcome(lifesat4 lifesat5 did_lifesat) kernel kerneltype(normal) bw(0.005) common
ate

psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4,
outcome(lifesat4 lifesat5 did_lifesat) neighbor(2) caliper(.01) common ate
bootstrap r(att), reps(50): psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4
pvhi4 shgood4 adl4 city4, outcome(lifesat4 lifesat5 did_lifesat) neighbor(2) caliper(.01) common ate

psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4,
outcome(lifesat4 lifesat5 did_lifesat) neighbor(5) caliper(.01) common ate
bootstrap r(att), reps(50): psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4
pvhi4 shgood4 adl4 city4, outcome(lifesat4 lifesat5 did_lifesat) neighbor(5) caliper(.01) common ate


*******************
***** Table 5 *****
*******************

*** by age ***
psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4 if
(age4<=70), outcome(econsat4 econsat5 did_econsat) kernel kerneltype(normal) bw(0.01) common ate
bootstrap r(att), reps(50): psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4
pvhi4 shgood4 adl4 city4 if (age4<=70), outcome(econsat4 econsat5 did_econsat) kernel kerneltype(normal) bw(0.01)
common ate
psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4 if
(age4>70), outcome(econsat4 econsat5 did_econsat) kernel kerneltype(normal) bw(0.01) common ate
bootstrap r(att), reps(50): psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4
pvhi4 shgood4 adl4 city4 if (age4>70), outcome(econsat4 econsat5 did_econsat) kernel kerneltype(normal) bw(0.01)
common ate

psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4 if
(age4<=70), outcome(hlthsat4 hlthsat5 did_hlthsat) kernel kerneltype(normal) bw(0.01) common ate
bootstrap r(att), reps(50): psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4
pvhi4 shgood4 adl4 city4 if (age4<=70), outcome(hlthsat4 hlthsat5 did_hlthsat) kernel kerneltype(normal) bw(0.01)
common ate
psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4 if
(age4>70), outcome(hlthsat4 hlthsat5 did_hlthsat) kernel kerneltype(normal) bw(0.01) common ate
bootstrap r(att), reps(50): psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4
pvhi4 shgood4 adl4 city4 if (age4>70), outcome(hlthsat4 hlthsat5 did_hlthsat) kernel kerneltype(normal) bw(0.01)
common ate

psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4 if
(age4<=70), outcome(chilsat4 chilsat5 did_chilsat) kernel kerneltype(normal) bw(0.01) common ate
```

```
bootstrap r(att), reps(50): psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4
pvhi4 shgood4 adl4 city4 if (age4<=70), outcome(chilsat4 chilsat5 did_chilsat) kernel kerneltype(normal) bw(0.01)
common ate
psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4 if
(age4>70), outcome(chilsat4 chilsat5 did_chilsat) kernel kerneltype(normal) bw(0.01) common ate
bootstrap r(att), reps(50): psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4
pvhi4 shgood4 adl4 city4 if (age4>70), outcome(chilsat4 chilsat5 did_chilsat) kernel kerneltype(normal) bw(0.01)
common ate

psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4 if
(age4<=70), outcome(lifesat4 lifesat5 did_lifesat) kernel kerneltype(normal) bw(0.01) common ate
bootstrap r(att), reps(50): psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4
pvhi4 shgood4 adl4 city4 if (age4<=70), outcome(lifesat4 lifesat5 did_lifesat) kernel kerneltype(normal) bw(0.01)
common ate
psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4 if
(age4>70), outcome(lifesat4 lifesat5 did_lifesat) kernel kerneltype(normal) bw(0.01) common ate
bootstrap r(att), reps(50): psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4
pvhi4 shgood4 adl4 city4 if (age4>70), outcome(lifesat4 lifesat5 did_lifesat) kernel kerneltype(normal) bw(0.01)
common ate


*** by gender ***
psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4 if
(female4==1), outcome(econsat4 econsat5 did_econsat) kernel kerneltype(normal) bw(0.01) common ate
bootstrap r(att), reps(50): psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4
pvhi4 shgood4 adl4 city4 if (female4==1), outcome(econsat4 econsat5 did_econsat) kernel kerneltype(normal) bw(0.01)
common ate
psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4 if
(female4==0), outcome(econsat4 econsat5 did_econsat) kernel kerneltype(normal) bw(0.01) common ate
bootstrap r(att), reps(50): psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4
pvhi4 shgood4 adl4 city4 if (female4==0), outcome(econsat4 econsat5 did_econsat) kernel kerneltype(normal) bw(0.01)
common ate

psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4 if
(female4==1), outcome(hlthsat4 hlthsat5 did_hlthsat) kernel kerneltype(normal) bw(0.01) common ate
bootstrap r(att), reps(50): psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4
pvhi4 shgood4 adl4 city4 if (female4==1), outcome(hlthsat4 hlthsat5 did_hlthsat) kernel kerneltype(normal) bw(0.01)
common ate
psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4 if
(female4==0), outcome(hlthsat4 hlthsat5 did_hlthsat) kernel kerneltype(normal) bw(0.01) common ate
bootstrap r(att), reps(50): psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4
pvhi4 shgood4 adl4 city4 if (female4==0), outcome(hlthsat4 hlthsat5 did_hlthsat) kernel kerneltype(normal) bw(0.01)
common ate

psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4 if
(female4==1), outcome(chilsat4 chilsat5 did_chilsat) kernel kerneltype(normal) bw(0.01) common ate
bootstrap r(att), reps(50): psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4
pvhi4 shgood4 adl4 city4 if (female4==1), outcome(chilsat4 chilsat5 did_chilsat) kernel kerneltype(normal) bw(0.01)
common ate
psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4 if
(female4==0), outcome(chilsat4 chilsat5 did_chilsat) kernel kerneltype(normal) bw(0.01) common ate
bootstrap r(att), reps(50): psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4
pvhi4 shgood4 adl4 city4 if (female4==0), outcome(chilsat4 chilsat5 did_chilsat) kernel kerneltype(normal) bw(0.01)
common ate

psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4 if
(female4==1), outcome(lifesat4 lifesat5 did_lifesat) kernel kerneltype(normal) bw(0.01) common ate
bootstrap r(att), reps(50): psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4
pvhi4 shgood4 adl4 city4 if (female4==1), outcome(lifesat4 lifesat5 did_lifesat) kernel kerneltype(normal) bw(0.01)
common ate
psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4 if
(female4==0), outcome(lifesat4 lifesat5 did_lifesat) kernel kerneltype(normal) bw(0.01) common ate
bootstrap r(att), reps(50): psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4
pvhi4 shgood4 adl4 city4 if (female4==0), outcome(lifesat4 lifesat5 did_lifesat) kernel kerneltype(normal) bw(0.01)
common ate


*** by marital status ***
```

```
psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4 if
(marr4==1), outcome(econsat4 econsat5 did_econsat) kernel kerneltype(normal) bw(0.01) common ate
bootstrap r(att), reps(50): psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4
pvhi4 shgood4 adl4 city4 if (marr4==1), outcome(econsat4 econsat5 did_econsat) kernel kerneltype(normal) bw(0.01)
common ate
psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4 if
(marr4==0), outcome(econsat4 econsat5 did_econsat) kernel kerneltype(normal) bw(0.01) common ate
bootstrap r(att), reps(50): psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4
pvhi4 shgood4 adl4 city4 if (marr4==0), outcome(econsat4 econsat5 did_econsat) kernel kerneltype(normal) bw(0.01)
common ate

psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4 if
(marr4==1), outcome(hlthsat4 hlthsat5 did_hlthsat) kernel kerneltype(normal) bw(0.01) common ate
bootstrap r(att), reps(50): psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4
pvhi4 shgood4 adl4 city4 if (marr4==1), outcome(hlthsat4 hlthsat5 did_hlthsat) kernel kerneltype(normal) bw(0.01)
common ate
psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4 if
(marr4==0), outcome(hlthsat4 hlthsat5 did_hlthsat) kernel kerneltype(normal) bw(0.01) common ate
bootstrap r(att), reps(50): psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4
pvhi4 shgood4 adl4 city4 if (marr4==0), outcome(hlthsat4 hlthsat5 did_hlthsat) kernel kerneltype(normal) bw(0.01)
common ate

psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4 if
(marr4==1), outcome(chilsat4 chilsat5 did_chilsat) kernel kerneltype(normal) bw(0.01) common ate
bootstrap r(att), reps(50): psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4
pvhi4 shgood4 adl4 city4 if (marr4==1), outcome(chilsat4 chilsat5 did_chilsat) kernel kerneltype(normal) bw(0.01)
common ate
psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4 if
(marr4==0), outcome(chilsat4 chilsat5 did_chilsat) kernel kerneltype(normal) bw(0.01) common ate
bootstrap r(att), reps(50): psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4
pvhi4 shgood4 adl4 city4 if (marr4==0), outcome(chilsat4 chilsat5 did_chilsat) kernel kerneltype(normal) bw(0.01)
common ate

psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4 if
(marr4==1), outcome(lifesat4 lifesat5 did_lifesat) kernel kerneltype(normal) bw(0.01) common ate
bootstrap r(att), reps(50): psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4
pvhi4 shgood4 adl4 city4 if (marr4==1), outcome(lifesat4 lifesat5 did_lifesat) kernel kerneltype(normal) bw(0.01)
common ate
psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4 if
(marr4==0), outcome(lifesat4 lifesat5 did_lifesat) kernel kerneltype(normal) bw(0.01) common ate
bootstrap r(att), reps(50): psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4
pvhi4 shgood4 adl4 city4 if (marr4==0), outcome(lifesat4 lifesat5 did_lifesat) kernel kerneltype(normal) bw(0.01)
common ate


*** by income ***
sum hhinc4 if (econsat4!=.), detail
psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4 if
(hhinc4<=r(p25)), outcome(econsat4 econsat5 did_econsat) kernel kerneltype(normal) bw(0.01) common ate
bootstrap r(att), reps(50): psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4
pvhi4 shgood4 adl4 city4 if (hhinc4<=r(p25)), outcome(econsat4 econsat5 did_econsat) kernel kerneltype(normal)
bw(0.01) common ate
sum hhinc4 if (econsat4!=.), detail
psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4 if
(hhinc4 > r(p25)), outcome(econsat4 econsat5 did_econsat) kernel kerneltype(normal) bw(0.01) common ate
bootstrap r(att), reps(50): psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4
pvhi4 shgood4 adl4 city4 if (hhinc4 > r(p25)), outcome(econsat4 econsat5 did_econsat) kernel kerneltype(normal)
bw(0.01) common ate

sum hhinc4 if (econsat4!=.), detail
psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4 if
(hhinc4<=r(p25)), outcome(hlthsat4 hlthsat5 did_hlthsat) kernel kerneltype(normal) bw(0.01) common ate
bootstrap r(att), reps(50): psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4
pvhi4 shgood4 adl4 city4 if (hhinc4<=r(p25)), outcome(hlthsat4 hlthsat5 did_hlthsat) kernel kerneltype(normal)
bw(0.01) common ate
sum hhinc4 if (econsat4!=.), detail
psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4 if
(hhinc4 > r(p25)), outcome(hlthsat4 hlthsat5 did_hlthsat) kernel kerneltype(normal) bw(0.01) common ate
```

```
bootstrap r(att), reps(50): psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4
pvhi4 shgood4 adl4 city4 if (hhinc4 > r(p25)), outcome(hlthsat4 hlthsat5 did_hlthsat) kernel kerneltype(normal)
bw(0.01) common ate

sum hhinc4 if (econsat4!=.), detail
psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4 if
(hhinc4<=r(p25)), outcome(chilsat4 chilsat5 did_chilsat) kernel kerneltype(normal) bw(0.01) common ate
bootstrap r(att), reps(50): psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4
pvhi4 shgood4 adl4 city4 if (hhinc4<=r(p25)), outcome(chilsat4 chilsat5 did_chilsat) kernel kerneltype(normal)
bw(0.01) common ate
sum hhinc4 if (econsat4!=.), detail
psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4 if
(hhinc4 > r(p25)), outcome(chilsat4 chilsat5 did_chilsat) kernel kerneltype(normal) bw(0.01) common ate
bootstrap r(att), reps(50): psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4
pvhi4 shgood4 adl4 city4 if (hhinc4 > r(p25)), outcome(chilsat4 chilsat5 did_chilsat) kernel kerneltype(normal)
bw(0.01) common ate

sum hhinc4 if (econsat4!=.), detail
psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4 if
(hhinc4<=r(p25)), outcome(lifesat4 lifesat5 did_lifesat) kernel kerneltype(normal) bw(0.01) common ate
bootstrap r(att), reps(50): psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4
pvhi4 shgood4 adl4 city4 if (hhinc4<=r(p25)), outcome(lifesat4 lifesat5 did_lifesat) kernel kerneltype(normal)
bw(0.01) common ate
sum hhinc4 if (econsat4!=.), detail
psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4 if
(hhinc4 > r(p25)), outcome(lifesat4 lifesat5 did_lifesat) kernel kerneltype(normal) bw(0.01) common ate
bootstrap r(att), reps(50): psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4
pvhi4 shgood4 adl4 city4 if (hhinc4 > r(p25)), outcome(lifesat4 lifesat5 did_lifesat) kernel kerneltype(normal)
bw(0.01) common ate


*******************
***** Table 6 *****
*******************
use "C:\Research\boap_qol\Data\klosa_wide.dta", clear
do "C:\Research\boap_qol\Data\cleaning_wide.do"
psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4,
outcome(econsat4 econsat5 did_econsat) kernel kerneltype(normal) bw(0.01) common ate
drop if (_support==0)
keep pid _weight
save "C:\Research\boap_qol\Data\matched_pid.dta", replace

use "C:\Research\boap_qol\Data\klosa_long.dta", clear
merge m:1 pid using "C:\Research\boap_qol\Data\matched_pid.dta"
keep if (age_elig==1)
drop if (year==1)
drop if missing(econsat)
bys pid (year): keep if _N==4

*reg econsat i.treat##ib5.year [aw=_weight], cluster(pid)
*test 1.treat#2.year=1.treat#3.year=1.treat#4.year=0
reg econsat i.treat##ib4.year [aw=_weight] if (year!=5), cluster(pid)
test 1.treat#2.year=1.treat#3.year=0


use "C:\Research\boap_qol\Data\klosa_wide.dta", clear
do "C:\Research\boap_qol\Data\cleaning_wide.do"
psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4,
outcome(hlthsat4 hlthsat5 did_hlthsat) kernel kerneltype(normal) bw(0.01) common ate
drop if (_support==0)
keep pid _weight
save "C:\Research\boap_qol\Data\matched_pid.dta", replace

use "C:\Research\boap_qol\Data\klosa_long.dta", clear
merge m:1 pid using "C:\Research\boap_qol\Data\matched_pid.dta"
keep if (age_elig==1)
drop if (year==1)
drop if missing(hlthsat)
```

```
bys pid (year): keep if _N==4

*reg hlthsat i.treat##ib5.year [aw=_weight], cluster(pid)
*test 1.treat#2.year=1.treat#3.year=1.treat#4.year=0
reg hlthsat i.treat##ib4.year [aw=_weight] if (year!=5), cluster(pid)
test 1.treat#2.year=1.treat#3.year=0


use "C:\Research\boap_qol\Data\klosa_wide.dta", clear
do "C:\Research\boap_qol\Data\cleaning_wide.do"
psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4,
outcome(chilsat4 chilsat5 did_chilsat) kernel kerneltype(normal) bw(0.01) common ate
drop if (_support==0)
keep pid _weight
save "C:\Research\boap_qol\Data\matched_pid.dta", replace

use "C:\Research\boap_qol\Data\klosa_long.dta", clear
merge m:1 pid using "C:\Research\boap_qol\Data\matched_pid.dta"
keep if (age_elig==1)
drop if (year==1)
drop if missing(chilsat)
bys pid (year): keep if _N==4

*reg chilsat i.treat##ib5.year [aw=_weight], cluster(pid)
*test 1.treat#2.year=1.treat#3.year=1.treat#4.year=0
reg chilsat i.treat##ib4.year [aw=_weight] if (year!=5), cluster(pid)
test 1.treat#2.year=1.treat#3.year=0


use "C:\Research\boap_qol\Data\klosa_wide.dta", clear
do "C:\Research\boap_qol\Data\cleaning_wide.do"
psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4,
outcome(lifesat4 lifesat5 did_lifesat) kernel kerneltype(normal) bw(0.01) common ate
drop if (_support==0)
keep pid _weight
save "C:\Research\boap_qol\Data\matched_pid.dta", replace

use "C:\Research\boap_qol\Data\klosa_long.dta", clear
merge m:1 pid using "C:\Research\boap_qol\Data\matched_pid.dta"
keep if (age_elig==1)
drop if (year==1)
drop if missing(lifesat)
bys pid (year): keep if _N==4

*reg lifesat i.treat##ib5.year [aw=_weight], cluster(pid)
*test 1.treat#2.year=1.treat#3.year=1.treat#4.year=0
reg lifesat i.treat##ib4.year [aw=_weight] if (year!=5), cluster(pid)
test 1.treat#2.year=1.treat#3.year=0


*******************
***** Table 7 *****
*******************

*** wave3 -> wave4 ***
use "C:\Research\boap_qol\Data\klosa_wide.dta", clear
do "C:\Research\boap_qol\Data\cleaning_wide_wave34.do"

psmatch2 treat age3 age_sq3 female3 middle3 high3 marr3 ret3 hhinc3 hown3 pbhi3 pvhi3 shgood3 adl3 city3,
outcome(econsat3 econsat4 did_econsat) kernel kerneltype(normal) bw(0.01) common ate
psmatch2 treat age3 age_sq3 female3 middle3 high3 marr3 ret3 hhinc3 hown3 pbhi3 pvhi3 shgood3 adl3 city3,
outcome(econsat3 econsat4 did_econsat) kernel kerneltype(normal) bw(0.005) common ate
psmatch2 treat age3 age_sq3 female3 middle3 high3 marr3 ret3 hhinc3 hown3 pbhi3 pvhi3 shgood3 adl3 city3,
outcome(econsat3 econsat4 did_econsat) neighbor(2) caliper(.01) common ate
psmatch2 treat age3 age_sq3 female3 middle3 high3 marr3 ret3 hhinc3 hown3 pbhi3 pvhi3 shgood3 adl3 city3,
outcome(econsat3 econsat4 did_econsat) neighbor(5) caliper(.01) common ate

psmatch2 treat age3 age_sq3 female3 middle3 high3 marr3 ret3 hhinc3 hown3 pbhi3 pvhi3 shgood3 adl3 city3,
```

```
outcome(hlthsat3 hlthsat4 did_hlthsat) kernel kerneltype(normal) bw(0.01) common ate
psmatch2 treat age3 age_sq3 female3 middle3 high3 marr3 ret3 hhinc3 hown3 pbhi3 pvhi3 shgood3 adl3 city3,
outcome(hlthsat3 hlthsat4 did_hlthsat) kernel kerneltype(normal) bw(0.005) common ate
psmatch2 treat age3 age_sq3 female3 middle3 high3 marr3 ret3 hhinc3 hown3 pbhi3 pvhi3 shgood3 adl3 city3,
outcome(hlthsat3 hlthsat4 did_hlthsat) neighbor(2) caliper(.01) common ate
psmatch2 treat age3 age_sq3 female3 middle3 high3 marr3 ret3 hhinc3 hown3 pbhi3 pvhi3 shgood3 adl3 city3,
outcome(hlthsat3 hlthsat4 did_hlthsat) neighbor(5) caliper(.01) common ate

psmatch2 treat age3 age_sq3 female3 middle3 high3 marr3 ret3 hhinc3 hown3 pbhi3 pvhi3 shgood3 adl3 city3,
outcome(chilsat3 chilsat4 did_chilsat) kernel kerneltype(normal) bw(0.01) common ate
psmatch2 treat age3 age_sq3 female3 middle3 high3 marr3 ret3 hhinc3 hown3 pbhi3 pvhi3 shgood3 adl3 city3,
outcome(chilsat3 chilsat4 did_chilsat) kernel kerneltype(normal) bw(0.005) common ate
psmatch2 treat age3 age_sq3 female3 middle3 high3 marr3 ret3 hhinc3 hown3 pbhi3 pvhi3 shgood3 adl3 city3,
outcome(chilsat3 chilsat4 did_chilsat) neighbor(2) caliper(.01) common ate
psmatch2 treat age3 age_sq3 female3 middle3 high3 marr3 ret3 hhinc3 hown3 pbhi3 pvhi3 shgood3 adl3 city3,
outcome(chilsat3 chilsat4 did_chilsat) neighbor(5) caliper(.01) common ate

psmatch2 treat age3 age_sq3 female3 middle3 high3 marr3 ret3 hhinc3 hown3 pbhi3 pvhi3 shgood3 adl3 city3,
outcome(lifesat3 lifesat4 did_lifesat) kernel kerneltype(normal) bw(0.01) common ate
psmatch2 treat age3 age_sq3 female3 middle3 high3 marr3 ret3 hhinc3 hown3 pbhi3 pvhi3 shgood3 adl3 city3,
outcome(lifesat3 lifesat4 did_lifesat) kernel kerneltype(normal) bw(0.005) common ate
psmatch2 treat age3 age_sq3 female3 middle3 high3 marr3 ret3 hhinc3 hown3 pbhi3 pvhi3 shgood3 adl3 city3,
outcome(lifesat3 lifesat4 did_lifesat) neighbor(2) caliper(.01) common ate
psmatch2 treat age3 age_sq3 female3 middle3 high3 marr3 ret3 hhinc3 hown3 pbhi3 pvhi3 shgood3 adl3 city3,
outcome(lifesat3 lifesat4 did_lifesat) neighbor(5) caliper(.01) common ate


*** wave3 -> wave5 ***
use "C:\Research\boap_qol\Data\klosa_wide.dta", clear
do "C:\Research\boap_qol\Data\cleaning_wide_wave35.do"

psmatch2 treat age3 age_sq3 female3 middle3 high3 marr3 ret3 hhinc3 hown3 pbhi3 pvhi3 shgood3 adl3 city3,
outcome(econsat3 econsat5 did_econsat) kernel kerneltype(normal) bw(0.01) common ate
psmatch2 treat age3 age_sq3 female3 middle3 high3 marr3 ret3 hhinc3 hown3 pbhi3 pvhi3 shgood3 adl3 city3,
outcome(econsat3 econsat5 did_econsat) kernel kerneltype(normal) bw(0.005) common ate
psmatch2 treat age3 age_sq3 female3 middle3 high3 marr3 ret3 hhinc3 hown3 pbhi3 pvhi3 shgood3 adl3 city3,
outcome(econsat3 econsat5 did_econsat) neighbor(2) caliper(.01) common ate
psmatch2 treat age3 age_sq3 female3 middle3 high3 marr3 ret3 hhinc3 hown3 pbhi3 pvhi3 shgood3 adl3 city3,
outcome(econsat3 econsat5 did_econsat) neighbor(5) caliper(.01) common ate

psmatch2 treat age3 age_sq3 female3 middle3 high3 marr3 ret3 hhinc3 hown3 pbhi3 pvhi3 shgood3 adl3 city3,
outcome(hlthsat3 hlthsat5 did_hlthsat) kernel kerneltype(normal) bw(0.01) common ate
psmatch2 treat age3 age_sq3 female3 middle3 high3 marr3 ret3 hhinc3 hown3 pbhi3 pvhi3 shgood3 adl3 city3,
outcome(hlthsat3 hlthsat5 did_hlthsat) kernel kerneltype(normal) bw(0.005) common ate
psmatch2 treat age3 age_sq3 female3 middle3 high3 marr3 ret3 hhinc3 hown3 pbhi3 pvhi3 shgood3 adl3 city3,
outcome(hlthsat3 hlthsat5 did_hlthsat) neighbor(2) caliper(.01) common ate
psmatch2 treat age3 age_sq3 female3 middle3 high3 marr3 ret3 hhinc3 hown3 pbhi3 pvhi3 shgood3 adl3 city3,
outcome(hlthsat3 hlthsat5 did_hlthsat) neighbor(5) caliper(.01) common ate

psmatch2 treat age3 age_sq3 female3 middle3 high3 marr3 ret3 hhinc3 hown3 pbhi3 pvhi3 shgood3 adl3 city3,
outcome(chilsat3 chilsat5 did_chilsat) kernel kerneltype(normal) bw(0.01) common ate
psmatch2 treat age3 age_sq3 female3 middle3 high3 marr3 ret3 hhinc3 hown3 pbhi3 pvhi3 shgood3 adl3 city3,
outcome(chilsat3 chilsat5 did_chilsat) kernel kerneltype(normal) bw(0.005) common ate
psmatch2 treat age3 age_sq3 female3 middle3 high3 marr3 ret3 hhinc3 hown3 pbhi3 pvhi3 shgood3 adl3 city3,
outcome(chilsat3 chilsat5 did_chilsat) neighbor(2) caliper(.01) common ate
psmatch2 treat age3 age_sq3 female3 middle3 high3 marr3 ret3 hhinc3 hown3 pbhi3 pvhi3 shgood3 adl3 city3,
outcome(chilsat3 chilsat5 did_chilsat) neighbor(5) caliper(.01) common ate

psmatch2 treat age3 age_sq3 female3 middle3 high3 marr3 ret3 hhinc3 hown3 pbhi3 pvhi3 shgood3 adl3 city3,
outcome(lifesat3 lifesat5 did_lifesat) kernel kerneltype(normal) bw(0.01) common ate
psmatch2 treat age3 age_sq3 female3 middle3 high3 marr3 ret3 hhinc3 hown3 pbhi3 pvhi3 shgood3 adl3 city3,
outcome(lifesat3 lifesat5 did_lifesat) kernel kerneltype(normal) bw(0.005) common ate
psmatch2 treat age3 age_sq3 female3 middle3 high3 marr3 ret3 hhinc3 hown3 pbhi3 pvhi3 shgood3 adl3 city3,
outcome(lifesat3 lifesat5 did_lifesat) neighbor(2) caliper(.01) common ate
psmatch2 treat age3 age_sq3 female3 middle3 high3 marr3 ret3 hhinc3 hown3 pbhi3 pvhi3 shgood3 adl3 city3,
outcome(lifesat3 lifesat5 did_lifesat) neighbor(5) caliper(.01) common ate
```

```
*******************
***** Table 8 *****
*******************

*** False treatment group ***
use "C:\Research\boap_qol\Data\klosa_wide.dta", clear
gen did_hlthsat = hlthsat5 - hlthsat4
gen did_econsat = econsat5 - econsat4
gen did_chilsat = chilsat5 - chilsat4
gen did_lifesat = lifesat5 - lifesat4

keep if (age5<65 & age5!=.)

sum hhinc4, detail
sum hhinc5, detail
gen treat=(hhinc4<5127 & hhinc5<5000)

psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4,
outcome(econsat4 econsat5 did_econsat) kernel kerneltype(normal) bw(0.01) common ate
psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4,
outcome(econsat4 econsat5 did_econsat) kernel kerneltype(normal) bw(0.005) common ate
psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4,
outcome(econsat4 econsat5 did_econsat) neighbor(2) caliper(.01) common ate
psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4,
outcome(econsat4 econsat5 did_econsat) neighbor(5) caliper(.01) common ate

psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4,
outcome(hlthsat4 hlthsat5 did_hlthsat) kernel kerneltype(normal) bw(0.01) common ate
psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4,
outcome(hlthsat4 hlthsat5 did_hlthsat) kernel kerneltype(normal) bw(0.005) common ate
psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4,
outcome(hlthsat4 hlthsat5 did_hlthsat) neighbor(2) caliper(.01) common ate
psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4,
outcome(hlthsat4 hlthsat5 did_hlthsat) neighbor(5) caliper(.01) common ate

psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4,
outcome(chilsat4 chilsat5 did_chilsat) kernel kerneltype(normal) bw(0.01) common ate
psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4,
outcome(chilsat4 chilsat5 did_chilsat) kernel kerneltype(normal) bw(0.005) common ate
psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4,
outcome(chilsat4 chilsat5 did_chilsat) neighbor(2) caliper(.01) common ate
psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4,
outcome(chilsat4 chilsat5 did_chilsat) neighbor(5) caliper(.01) common ate

psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4,
outcome(lifesat4 lifesat5 did_lifesat) kernel kerneltype(normal) bw(0.01) common ate
psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4,
outcome(lifesat4 lifesat5 did_lifesat) kernel kerneltype(normal) bw(0.005) common ate
psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4,
outcome(lifesat4 lifesat5 did_lifesat) neighbor(2) caliper(.01) common ate
psmatch2 treat age4 age_sq4 female4 middle4 high4 marr4 ret4 hhinc4 hown4 pbhi4 pvhi4 shgood4 adl4 city4,
outcome(lifesat4 lifesat5 did_lifesat) neighbor(5) caliper(.01) common ate
```

5.4 Essay II: Computer Codes

```
********************
***** Input.do *****
********************
clear all
set more off
set maxvar 25000

use D:\Research\Smoking_klosa\Data\w01_main_k.dta, clear
merge 1:1 pid using "D:\Research\Smoking_klosa\Data\w02_main_k.dta"
```

```
drop _merge
merge 1:1 pid using "D:\Research\Smoking_klosa\Data\w03_main_k.dta"
drop _merge
merge 1:1 pid using "D:\Research\Smoking_klosa\Data\w04_main_k.dta"
drop _merge
merge 1:1 pid using "D:\Research\Smoking_klosa\Data\w05_main_k.dta"
drop _merge
save "D:\Research\Smoking_klosa\Data\klosa_merged", replace

#delimit;


/*
*****************************************************;
***** Discount factors (CPI All Urban Consumers) *****;
*****************************************************;
Year Annual average
2005 86.1
2006 88.1
2007 90.2
2008 94.5
2009 97.1
2010 100.0
2011 104.0
2012 106.3
2013 107.7
2014 109.0
*/
local discf1 1.23723;
local discf2 1.15344;
local discf3 1.09;
local discf4 1.0254;
local discf5 1;

*** Sampling weight ***;
gen wgta1=.;
forv i=2/4 {;
gen wgta`i'=w0`i'wgt01;
};
gen wgta5=w05wgt_p;

gen wgtb1=.;
forv i=2/4 {;
gen wgtb`i'=w0`i'wgt02;
};
gen wgtb5=w05wgt_c;

*** Interview date ***;
forv i=1/5 {;
gen intyr`i'=w0`i'mniw_y;
gen intmo`i'=w0`i'mniw_m;
};

gen finr1=.;
forv i=2/5 {;
gen finr`i'=w0`i'ea_resp;
};

********************************;
***** DEMOGRAPHIC VARIABLES *****;
********************************;

*** Age ***;
gen age1=w01a001_age;
forv i=2/5 {;
gen age`i'=w0`i'a002_age;
};
```

```
*** Gender ***;
forv i=1/5 {;
gen female`i'=(w0`i'gender1==5);
};

*** Education ***;
forv i=1/5 {;
gen lesshigh`i'=(w0`i'edu==1);
gen middle`i'=(w0`i'edu==2);
gen high`i'=(w0`i'edu==3);
gen coll`i'=(w0`i'edu==4);
};
forv i=1/5 {;
gen educ`i'=(w0`i'edu==3 | w0`i'edu==4);
};

*** Marital ***;
gen marr1=.;
replace marr1=1 if (w01a006==1);
replace marr1=0 if (w01a006>=2 & w01a006<=5);
forv i=2/5 {;
gen marr`i'=.;
replace marr`i'=1 if (w0`i'marital==1);
replace marr`i'=0 if (w0`i'marital>=2 & w0`i'marital<=5);
};

*** Region dummies ***;
forv i=1/5 {;
gen state`i'=w0`i'region1;
gen county`i'=w0`i'region2;
gen city`i'=w0`i'region3;
};

*** Residence format ***;
forv i=1/5 {;
gen house`i'=(w0`i'enu_type==1);
};

*** Number of live children ***;
gen nochld1=w01ba01;
forv i=2/5 {;
gen nochld`i'=w0`i'ba003;
};
forv i=1/5 {;
replace nochld`i'=. if (nochld`i'==-8 |  nochld`i'==-9);
replace nochld`i'=0 if (nochld`i'==.);
};

**************************;
***** Health variable *****;
**************************;

*** Disability ****;
gen disab1=(w01c002==1);
forv i=2/5 {;
gen disab`i'=(w0`i'c003==1);
};

*** Exercise ***;
gen exerc1=(w01c096==1);
gen exerc5=(w05c116==1);
forv i=2/4 {;
gen exerc`i'=(w0`i'c108==1);
};

*** SR health ****;
forv i=1/5 {;
gen srhlth`i'=w0`i'c001;
```

```
replace srhlth`i'=. if (srhlth`i'==-8);
replace srhlth`i'=6-srhlth`i';
};

*** SR health (relative to the previous wave) ****;
forv i=2/5 {;
gen srhlth_r`i'=w0`i'c002;
replace srhlth_r`i'=. if (srhlth_r`i'==-8 | srhlth_r`i'==-9);
};
gen srhlth_r1=.;


*** Onset of chronic conditions ****;
gen highbp1=(w01c005==1);
replace highbp1=. if (w01c005!=1 & w01c005!=5);
gen diabete1=(w01c009==1);
replace highbp1=. if (w01c009!=1 & w01c009!=5);
gen cancr1=(w01c013==1);
replace highbp1=. if (w01c013!=1 & w01c013!=5);
gen lung1=(w01c019==1);
replace highbp1=. if (w01c019!=1 & w01c019!=5);
gen liver1=(w01c023==1);
replace highbp1=. if (w01c023!=1 & w01c023!=5);
gen heart1=(w01c027==1);
replace highbp1=. if (w01c027!=1 & w01c027!=5);
gen brain1=(w01c031==1);
replace highbp1=. if (w01c031!=1 & w01c031!=5);
gen psych1=(w01c035==1);
replace highbp1=. if (w01c035!=1 & w01c035!=5);
gen arthr1=(w01c039==1);
replace highbp1=. if (w01c039!=1 & w01c039!=5);

forv i=2/5 {;
gen highbp`i'=(w0`i'c006==1);
replace highbp`i'=. if (w0`i'c006!=1 & w0`i'c006!=5);
gen diabete`i'=(w0`i'c011==1);
replace diabete`i'=. if (w0`i'c011!=1 & w0`i'c011!=5);
gen cancr`i'=(w0`i'c016==1);
replace cancr`i'=. if (w0`i'c016!=1 & w0`i'c016!=5);
gen lung`i'=(w0`i'c023==1);
replace lung`i'=. if (w0`i'c023!=1 & w0`i'c023!=5);
gen liver`i'=(w0`i'c028==1);
replace liver`i'=. if (w0`i'c028!=1 & w0`i'c028!=5);
gen heart`i'=(w0`i'c033==1);
replace heart`i'=. if (w0`i'c033!=1 & w0`i'c033!=5);
gen brain`i'=(w0`i'c038==1);
replace brain`i'=. if (w0`i'c038!=1 & w0`i'c038!=5);
gen psych`i'=(w0`i'c043==1);
replace psych`i'=. if (w0`i'c043!=1 & w0`i'c043!=5);
gen arthr`i'=(w0`i'c048==1);
replace arthr`i'=. if (w0`i'c048!=1 & w0`i'c048!=5);
};

*** Chronic conditios ***;
gen c_highbp1=highbp1;
gen c_highbp2=(highbp1==1 | highbp2==1);
gen c_highbp3=(highbp1==1 | highbp2==1 | highbp3==1);
gen c_highbp4=(highbp1==1 | highbp2==1 | highbp3==1 | highbp4==1);
gen c_highbp5=(highbp1==1 | highbp2==1 | highbp3==1 | highbp4==1 | highbp5==1);

gen c_diabete1=diabete1;
gen c_diabete2=(diabete1==1 | diabete2==1);
gen c_diabete3=(diabete1==1 | diabete2==1 | diabete3==1);
gen c_diabete4=(diabete1==1 | diabete2==1 | diabete3==1 | diabete4==1);
gen c_diabete5=(diabete1==1 | diabete2==1 | diabete3==1 | diabete4==1 | diabete5==1);

gen c_cancr1=cancr1;
gen c_cancr2=(cancr1==1 | cancr2==1);
```

```
gen c_cancr3=(cancr1==1 | cancr2==1 | cancr3==1);
gen c_cancr4=(cancr1==1 | cancr2==1 | cancr3==1 | cancr4==1);
gen c_cancr5=(cancr1==1 | cancr2==1 | cancr3==1 | cancr4==1 | cancr5==1);

gen c_lung1=lung1;
gen c_lung2=(lung1==1 | lung2==1);
gen c_lung3=(lung1==1 | lung2==1 | lung3==1);
gen c_lung4=(lung1==1 | lung2==1 | lung3==1 | lung4==1);
gen c_lung5=(lung1==1 | lung2==1 | lung3==1 | lung4==1 | lung5==1);

gen c_liver1=liver1;
gen c_liver2=(liver1==1 | liver2==1);
gen c_liver3=(liver1==1 | liver2==1 | liver3==1);
gen c_liver4=(liver1==1 | liver2==1 | liver3==1 | liver4==1);
gen c_liver5=(liver1==1 | liver2==1 | liver3==1 | liver4==1 | liver5==1);

gen c_heart1=heart1;
gen c_heart2=(heart1==1 | heart2==1);
gen c_heart3=(heart1==1 | heart2==1 | heart3==1);
gen c_heart4=(heart1==1 | heart2==1 | heart3==1 | heart4==1);
gen c_heart5=(heart1==1 | heart2==1 | heart3==1 | heart4==1 | heart5==1);

gen c_brain1=brain1;
gen c_brain2=(brain1==1 | brain2==1);
gen c_brain3=(brain1==1 | brain2==1 | brain3==1);
gen c_brain4=(brain1==1 | brain2==1 | brain3==1 | brain4==1);
gen c_brain5=(brain1==1 | brain2==1 | brain3==1 | brain4==1 | brain5==1);

gen c_psych1=psych1;
gen c_psych2=(psych1==1 | psych2==1);
gen c_psych3=(psych1==1 | psych2==1 | psych3==1);
gen c_psych4=(psych1==1 | psych2==1 | psych3==1 | psych4==1);
gen c_psych5=(psych1==1 | psych2==1 | psych3==1 | psych4==1 | psych5==1);

gen c_arthr1=arthr1;
gen c_arthr2=(arthr1==1 | arthr2==1);
gen c_arthr3=(arthr1==1 | arthr2==1 | arthr3==1);
gen c_arthr4=(arthr1==1 | arthr2==1 | arthr3==1 | arthr4==1);
gen c_arthr5=(arthr1==1 | arthr2==1 | arthr3==1 | arthr4==1 | arthr5==1);


*** BMI and obesity ***;
forv i=1/5 {;
gen bmi`i'=w0`i'bmi;
gen obs`i'=(w0`i'bmi>=30);
};

*** Smoking and drinking ***;
forv i=1/5 {;
gen csmok`i'=(w0`i'smoke==2);
gen psmok`i'=(w0`i'smoke==1);
gen nsmok`i'=(w0`i'smoke==0);

gen smk_term`i'=w0`i'smkterm;
gen alc_term`i'=w0`i'alcterm;

gen drnk`i'=(w0`i'alc==3);
};

gen smk_num1=w01c105;
gen smk_num5=w05c127;
forv i=2/4 {;
gen smk_num`i'=w0`i'c119;
};
forv i=1/5 {;
replace smk_num`i'=. if (smk_num`i'==-8 | smk_num`i'==-9);
};
```

```
gen smk_numm1=w01c107;
gen smk_numm5=w05c128;
forv i=2/4 {;
gen smk_numm`i'=w0`i'c120;
};
forv i=1/5 {;
replace smk_numm`i'=. if (smk_numm`i'==-8 | smk_numm`i'==-9);
};

gen smk_styr1=w01c106y;
gen smk_styr5=w05c126y;
forv i=2/4 {;
gen smk_styr`i'=w0`i'c118y;
};
gen alc_styr1=w01c113y;
gen alc_styr5=w05c132y;
forv i=2/4 {;
gen alc_styr`i'=w0`i'c124y;
};
forv i=1/5 {;
replace smk_styr`i'=. if (smk_styr`i'==-8 | smk_styr`i'==-9);
replace alc_styr`i'=. if (alc_styr`i'==-8 | alc_styr`i'==-9);
};

replace w01c108y=. if (w01c108y==-8 | w01c108y==-9);
replace w02c121y=. if (w02c121y==-8 | w02c121y==-9);
replace w03c121y=. if (w03c121y==-8 | w03c121y==-9);
replace w04c121y=. if (w04c121y==-8 | w04c121y==-9);
replace w05c129y=. if (w05c129y==-8 | w05c129y==-9);

gen quityr1=intyr1-w01c108y;
gen quityr2=intyr2-w02c121y;
gen quityr3=intyr3-w03c121y;
gen quityr4=intyr4-w04c121y;
gen quityr5=intyr5-w05c129y;

*** ADL & IADL ***;
forv i=1/5 {;
gen adl`i'=w0`i'adl;
gen iadl`i'=w0`i'iadl;
};

*** Cognitive score ***;
forv i=1/5 {;
gen cog`i'=w0`i'mmse;
gen cogg`i'=w0`i'mmseg;
};


gen w01c450=w01cd50;
gen w01c401=w01cd01;
gen w01c402=w01cd02;
gen w01c403=w01cd03;
gen w01c404=w01cd04;
gen w01c405=w01cd05;
gen w01c406=w01cd06;
gen w01c407=w01cd07;
gen w01c408=w01cd08;
gen w01c409=w01cd09;
gen w01c410=w01cd10;
gen w01c411=w01cd11;
gen w01c412=w01cd12;
gen w01c413=w01cd13;
gen w01c414=w01cd14;
gen w01c415=w01cd15;
gen w01c416=w01cd16;
gen w01c417=w01cd17;
gen w01c418=w01cd18;
```

```
gen w01c419=w01cd19;

forv i=1/5 {;
gen proxy`i'=(w0`i'c450==1);
};

forv i=1/5 {;
gen msea`i'=.;
replace msea`i'=1 if (w0`i'c401==1);
replace msea`i'=2 if (w0`i'c401==2);
replace msea`i'=3 if (w0`i'c401==3);
replace msea`i'=0 if (w0`i'c401==5 | w0`i'c401==-8 | w0`i'c401==-9);
gen mseb`i'=(w0`i'c402==1);
gen msec`i'=(w0`i'c403==1);

gen msed`i'=(w0`i'c404==1);
gen msee`i'=.;
replace msee`i'=1 if (w0`i'c405==1);
replace msee`i'=2 if (w0`i'c405==2);
replace msee`i'=3 if (w0`i'c405==3);
replace msee`i'=4 if (w0`i'c405==4);
replace msee`i'=0 if (w0`i'c405==5 | w0`i'c405==-8 | w0`i'c405==-9);

gen msef`i'=.;
replace msef`i'=1 if (w0`i'c406==1);
replace msef`i'=2 if (w0`i'c406==2);
replace msef`i'=3 if (w0`i'c406==3);
replace msef`i'=0 if (w0`i'c406==5 | w0`i'c406==-8 | w0`i'c406==-9);

gen mseg`i'=(w0`i'c407==1);
gen mseh`i'=(w0`i'c408==1);
gen msei`i'=(w0`i'c409==1);
gen msej`i'=(w0`i'c410==1);
gen msek`i'=(w0`i'c411==1);

gen msel`i'=.;
replace msel`i'=1 if (w0`i'c412==1);
replace msel`i'=2 if (w0`i'c412==2);
replace msel`i'=3 if (w0`i'c412==3);
replace msel`i'=0 if (w0`i'c412==5 | w0`i'c412==-8 | w0`i'c412==-9);

gen msem`i'=(w0`i'c413==1);
gen msen`i'=(w0`i'c414==1);
gen mseo`i'=(w0`i'c415==1);

gen msep`i'=.;
replace msep`i'=1 if (w0`i'c416==1);
replace msep`i'=2 if (w0`i'c416==2);
replace msep`i'=3 if (w0`i'c416==3);
replace msep`i'=0 if (w0`i'c416==5 | w0`i'c416==-8 | w0`i'c416==-9);

gen mseq`i'=(w0`i'c417==1 | w0`i'c417==3);
gen mser`i'=(w0`i'c418==1);
gen mses`i'=(w0`i'c419==1);
};

*** Grip strength ***;
forv i=1/5 {;
gen grip`i'=w0`i'mgrip;
};

*********************;
***** Employment *****;
*********************;

*** Employment status ***;
forv i=1/5 {;
gen work`i'=(w0`i'd001==1);
```

```
gen empl`i'=(w0`i'ecoact==1);
};

*****************************;
******* Income and Asset *****;
*****************************;

*** Labor income ***;
forv i=1/5 {;
gen linc`i'=w0`i'e003;
replace linc`i'=. if (w0`i'e003==-8 | w0`i'e003==-9);
};

*** Total HH income ***;
forv i=1/4 {;
gen hhinc`i'=w0`i'e126;
replace hhinc`i'=. if (w0`i'e126==-8 | w0`i'e126==-9);
};
gen hhinc5=w05e147;
replace hhinc5=. if (w05e147==-8 | w05e147==-9);

*** Total HH wealth ***;
forv i=1/4 {;
*** Asset ***;
replace w0`i'f005=. if (w0`i'f005==-8 | w0`i'f005==-9);
replace w0`i'f031=. if (w0`i'f031==-8 | w0`i'f031==-9);
replace w0`i'f037=. if (w0`i'f037==-8 | w0`i'f037==-9);
replace w0`i'f050=. if (w0`i'f050==-8 | w0`i'f050==-9);
replace w0`i'f078=. if (w0`i'f078==-8 | w0`i'f078==-9);
replace w0`i'f085=. if (w0`i'f085==-8 | w0`i'f085==-9);
replace w0`i'f092=. if (w0`i'f092==-8 | w0`i'f092==-9);
replace w0`i'f099=. if (w0`i'f099==-8 | w0`i'f099==-9);
replace w0`i'f106=. if (w0`i'f106==-8 | w0`i'f106==-9);
replace w0`i'f139=. if (w0`i'f139==-8 | w0`i'f139==-9);
replace w0`i'f146=. if (w0`i'f146==-8 | w0`i'f146==-9);
replace w0`i'f173=. if (w0`i'f173==-8 | w0`i'f173==-9);
replace w0`i'f180=. if (w0`i'f180==-8 | w0`i'f180==-9);

*** Debt ***;
replace w0`i'f198=. if (w0`i'f198==-8 | w0`i'f198==-9);
replace w0`i'f198=(w0`i'f198*-1);
replace w0`i'f205=. if (w0`i'f205==-8 | w0`i'f205==-9);
replace w0`i'f205=(w0`i'f205*-1);
replace w0`i'f212=. if (w0`i'f212==-8 | w0`i'f212==-9);
replace w0`i'f212=(w0`i'f212*-1);
replace w0`i'f220=. if (w0`i'f220==-8 | w0`i'f220==-9);
replace w0`i'f220=(w0`i'f220*-1);
};

forv i=1/4 {;
*** Total financial wealth ***;
egen totfw`i'=rowtotal(w0`i'f085 w0`i'f092 w0`i'f099 w0`i'f106 w0`i'f139 w0`i'f146);
*replace totfw`i'=. if (w0`i'f085==. & w0`i'f092==. & w0`i'f099==. & w0`i'f106==. & w0`i'f139==. & w0`i'f146==.);
*gen totfw`i'=w0`i'f085 + w0`i'f092 + w0`i'f099 + w0`i'f106 + w0`i'f139 + w0`i'f146;
*** Total wealth ***;
egen totnwa`i'=rowtotal(w0`i'f005 w0`i'f031 w0`i'f037 w0`i'f050 w0`i'f078 w0`i'f085 w0`i'f092 w0`i'f099 w0`i'f106
w0`i'f139 w0`i'f146 w0`i'f173 w0`i'f180 w0`i'f198 w0`i'f205 w0`i'f212 w0`i'f220);
*replace totnwa`i'=. if (w0`i'f005==. & w0`i'f031==. & w0`i'f037==. & w0`i'f050==. & w0`i'f078==. & w0`i'f085==.
& w0`i'f092==. & w0`i'f099==. & w0`i'f106==. & w0`i'f139==. & w0`i'f146==. & w0`i'f173==. & w0`i'f180==. & w0`i'f198==.
& w0`i'f205==. & w0`i'f212==. & w0`i'f220==.);
*gen totnwa`i'=w0`i'f005 + w0`i'f031 + w0`i'f037 + w0`i'f050 + w0`i'f078 + w0`i'f085 + w0`i'f092 + w0`i'f099 +
w0`i'f106 + w0`i'f139 + w0`i'f146 + w0`i'f173 + w0`i'f180 + w0`i'f198 + w0`i'f205 + w0`i'f212 + w0`i'f220;
};

*** Asset ***;
replace w05f007=. if (w05f007==-8 | w05f007==-9);
replace w05f035=. if (w05f035==-8 | w05f035==-9);
replace w05f043=. if (w05f043==-8 | w05f043==-9);
```

```
replace w05f058=. if (w05f058==-8 | w05f058==-9);
replace w05f086=. if (w05f086==-8 | w05f086==-9);
replace w05f095=. if (w05f095==-8 | w05f095==-9);
replace w05f102=. if (w05f102==-8 | w05f102==-9);
replace w05f109=. if (w05f109==-8 | w05f109==-9);
replace w05f116=. if (w05f116==-8 | w05f116==-9);
replace w05f139=. if (w05f139==-8 | w05f139==-9);
replace w05f146=. if (w05f146==-8 | w05f146==-9);
replace w05f175=. if (w05f175==-8 | w05f175==-9);
replace w05f182=. if (w05f182==-8 | w05f182==-9);

*** Debt ***;
replace w05f206=. if (w05f206==-8 | w05f206==-9);
replace w05f206=(w05f206*-1);
replace w05f213=. if (w05f213==-8 | w05f213==-9);
replace w05f213=(w05f213*-1);
replace w05f220=. if (w05f220==-8 | w05f220==-9);
replace w05f220=(w05f220*-1);
replace w05f228=. if (w05f228==-8 | w05f228==-9);
replace w05f228=(w05f228*-1);

*** Total financial wealth ***;
egen totfw5=rowtotal(w05f095 w05f102 w05f109 w05f116 w05f139 w05f146);
*replace totfw5=. if (w05f095==. & w05f102==. & w05f109==. & w05f116==. & w05f139==. & w05f146==.);
*** Total wealth ***;
egen totnwa5=rowtotal(w05f007 w05f035 w05f043 w05f058 w05f086 w05f095 w05f102 w05f109 w05f116 w05f139 w05f146
w05f175 w05f182 w05f206 w05f213 w05f220 w05f228);
*replace totnwa5=. if (w05f007==. & w05f035==. & w05f043==. & w05f058==. & w05f086==. & w05f095==. & w05f102==.
& w05f109==. & w05f116==. & w05f139==. & w05f146==. & w05f175==. & w05f182==. & w05f206==. & w05f213==. & w05f220==.
& w05f228==.);

*** Saving ***;
gen avgsav1=.;
forv i=2/4 {;
gen avgsav`i'=w0`i'e251;
replace avgsav`i'=. if (w0`i'e251==-8 | w0`i'e251==-9);
};
gen avgsav5=w05e281;
replace avgsav5=. if (w05e281==-8 | w05e281==-9);
forv i=1/5 {;
replace avgsav`i'=(12*avgsav`i');
};

forv i=1/5 {;
replace linc`i'=linc`i'*`discf`i'';
replace hhinc`i'=hhinc`i'*`discf`i'';
replace totnwa`i'=totnwa`i'*`discf`i'';
replace totfw`i'=totfw`i'*`discf`i'';
replace avgsav`i'=avgsav`i'*`discf`i'';
};

********************************;
******* Consumption variable ****;
********************************;
forv i=2/5 {;
replace w0`i'e201=. if (w0`i'e201==-8 | w0`i'e201==-9);
replace w0`i'e207=. if (w0`i'e207==-8 | w0`i'e207==-9);
replace w0`i'e213=. if (w0`i'e213==-8 | w0`i'e213==-9);
replace w0`i'e219=. if (w0`i'e219==-8 | w0`i'e219==-9);
replace w0`i'e225=. if (w0`i'e225==-8 | w0`i'e225==-9);
replace w0`i'e231=. if (w0`i'e231==-8 | w0`i'e231==-9);
replace w0`i'e237=. if (w0`i'e237==-8 | w0`i'e237==-9);
replace w0`i'e243=. if (w0`i'e243==-8 | w0`i'e243==-9);
};

gen csa1=.;
gen csb1=.;
gen csc1=.;
```

```
gen csd1=.;
gen cse1=.;
gen csf1=.;
gen csg1=.;
gen csh1=.;

forv i=2/5 {;
gen csa`i'=w0`i'e201;
gen csb`i'=w0`i'e207;
gen csc`i'=w0`i'e213;
gen csd`i'=w0`i'e219;
gen cse`i'=w0`i'e225;
gen csf`i'=w0`i'e231;
gen csg`i'=w0`i'e237;
gen csh`i'=w0`i'e243;
};

forv i=2/5 {;
replace csa`i'=(csa`i'*`discf`i'')*12;
replace csb`i'=(csb`i'*`discf`i'')*12;
replace csc`i'=(csc`i'*`discf`i'')*12;
replace csd`i'=(csd`i'*`discf`i'')*12;
replace cse`i'=(cse`i'*`discf`i'')*12;
replace csf`i'=(csf`i'*`discf`i'')*12;
replace csg`i'=(csg`i'*`discf`i'')*12;
replace csh`i'=(csh`i'*`discf`i'')*12;
};

gen lesa1=.;
gen lesb1=.;
gen lesc1=.;
forv i=2/4 {;
gen lesa`i'=w0`i'g122;
gen lesb`i'=w0`i'g124;
gen lesc`i'=w0`i'g126;
};
gen lesa5=w05g034;
gen lesb5=w05g036;
gen lesc5=w05g038;

forv i=2/5 {;
replace lesa`i'=lesa`i'*`discf`i'';
replace lesb`i'=lesb`i'*`discf`i'';
replace lesc`i'=lesc`i'*`discf`i'';
};

gen les1=.;
forv i=2/5 {;
egen les`i'=rowtotal(lesa`i' lesb`i' lesc`i');
replace les`i'=. if (lesa`i'==. & lesb`i'==. & lesc`i'==.);
};

***** Consumption summary variables *****;

* food: csb+csc;
* foodex: csa+csb+csc;
* csmpa: csa+csb+csc+csh;
* csmpb: csa+csb+csc+csh+les;
* csmpc: csb+csc+les;
* csmpd: csa+csb+csc+les;
* csmpe: csa+csb+csc+csd+cse+csf+csg+csh;
* csmpf: csa+csb+csc+csd+cse+csf+csg+csh+les;

gen food1=.;
forv i=2/5 {;
egen food`i'=rowtotal(csb`i' csc`i');
replace food`i'=. if (csb`i'==. & csc`i'==.);
};
```

```
gen foodex1=.;
forv i=2/5 {;
egen foodex`i'=rowtotal(csa`i' csb`i' csc`i');
replace foodex`i'=. if (csa`i'==. & csb`i'==. & csc`i'==.);
};

gen csmpa1=.;
forv i=2/5 {;
egen csmpa`i'=rowtotal(csa`i' csb`i' csc`i' csh`i');
replace csmpa`i'=. if (csa`i'==. & csb`i'==. & csc`i'==. & csh`i'==.);
};

gen csmpb1=.;
forv i=2/5 {;
egen csmpb`i'=rowtotal(csa`i' csb`i' csc`i' csh`i' les`i');
replace csmpb`i'=. if (csa`i'==. & csb`i'==. & csc`i'==. & csh`i'==. & les`i'==.);
};

gen csmpc1=.;
forv i=2/5 {;
egen csmpc`i'=rowtotal(csb`i' csc`i' les`i');
replace csmpc`i'=. if (csb`i'==. & csc`i'==. & les`i'==.);
};

gen csmpd1=.;
forv i=2/5 {;
egen csmpd`i'=rowtotal(csa`i' csb`i' csc`i' les`i');
replace csmpd`i'=. if (csa`i'==. & csb`i'==. & csc`i'==. & les`i'==.);
};

gen csmpe1=.;
forv i=2/5 {;
egen csmpe`i'=rowtotal(csa`i' csb`i' csc`i' csd`i' cse`i' csf`i' csg`i' csh`i');
replace csmpe`i'=. if (csa`i'==. & csb`i'==. & csc`i'==. & csd`i'==. & cse`i'==. & csf`i'==. & csg`i'==. & csh`i'==.);
};

gen csmpf1=.;
forv i=2/5 {;
egen csmpf`i'=rowtotal(csa`i' csb`i' csc`i' csd`i' cse`i' csf`i' csg`i' csh`i' les`i');
replace csmpf`i'=. if (csa`i'==. & csb`i'==. & csc`i'==. & csd`i'==. & cse`i'==. & csf`i'==. & csg`i'==. & csh`i'==.
& les`i'==.);
};

reshape long //
wgta wgtb intyr intmo finr age female lesshigh middle high coll educ marr state county city house nochld //
disab exerc srhlth srhlth_r highbp diabete cancr lung liver heart brain psych arthr c_highbp c_diabete c_cancr
c_lung c_liver c_heart c_brain c_psych c_arthr bmi obs csmok psmok nsmok smk_term alc_term drnk smk_num smk_numm
smk_styr alc_styr quityr adl iadl proxy cog cogg msea mseb msec msed msee msef mseg mseh msei msej msek msel
msem msen mseo msep mseq mser mses grip //
work empl linc hhinc totnwa totfw avgsav csa csb csc csd cse csf csg csh lesa lesb lesc les food foodex csmpa
csmpb csmpc csmpd csmpe csmpf //
, i(pid) j(year);

*** Assign year value;
*replace year=2006 if (year==1);
*replace year=2008 if (year==2);
*replace year=2010 if (year==3);
*replace year=2012 if (year==4);
*replace year=2014 if (year==5);

sort pid hhid respid year;
keep pid hhid respid year ///
wgta wgtb intyr intmo finr age female lesshigh middle high coll educ marr state county city house nochld //
disab exerc srhlth srhlth_r highbp diabete cancr lung liver heart brain psych arthr c_highbp c_diabete c_cancr
c_lung c_liver c_heart c_brain c_psych c_arthr bmi obs csmok psmok nsmok smk_term alc_term drnk smk_num smk_numm
smk_styr alc_styr quityr adl iadl proxy cog cogg msea mseb msec msed msee msef mseg mseh msei msej msek msel
msem msen mseo msep mseq mser mses grip //
```

```
work empl linc hhinc totnwa totfw avgsav csa csb csc csd cse csf csg csh lesa lesb lesc les food foodex csmpa
csmpb csmpc csmpd csmpe csmpf;
order pid hhid respid year ///
wgta wgtb intyr intmo finr age female lesshigh middle high coll educ marr state county city house nochld //
disab exerc srhlth srhlth_r highbp diabete cancr lung liver heart brain psych arthr c_highbp c_diabete c_cancr
c_lung c_liver c_heart c_brain c_psych c_arthr bmi obs csmok psmok nsmok smk_term alc_term drnk smk_num smk_numm
smk_styr alc_styr quityr adl iadl proxy cog cogg msea mseb msec msed msee msef mseg mseh msei msej msek msel
msem msen mseo msep mseq mser mses grip //
work empl linc hhinc totnwa totfw avgsav csa csb csc csd cse csf csg csh lesa lesb lesc les food foodex csmpa
csmpb csmpc csmpd csmpe csmpf;

******************************;
***** Cognitive function *****;
******************************;

gen ortime=msea+mseb+msec;
gen orplace=msed+msee;
gen imrc=msef;
gen ser7=mseg+mseh+msei+msej+msek;
gen dlrc=msel;
gen langg=msem+msen+mseo+msep+mseq+mser;
gen visual=mses;

gen epsdc=imrc+dlrc;
gen shortm=imrc+dlrc+ser7;

gen orient=ortime+orplace;

drop cog;
gen cog=ortime+orplace+imrc+dlrc+ser7+langg+visual;

gen cog_sm=ortime+dlrc+ser7+visual;

gen cog_mi=ortime+dlrc+visual;

******************************;
***** Log-transformation *****;
******************************;
gen log_totnwa=.;
replace log_totnwa=-log((-1*totnwa)+.01) if totnwa<0;
replace log_totnwa=log(totnwa+.01) if totnwa>=0;
gen log_totfw=.;
replace log_totfw=-log((-1*totfw)+.01) if totfw<0;
replace log_totfw=log(totfw+.01) if totfw>=0;

gen log_csa=log(csa+.001);
gen log_csg=log(csg+.001);
gen log_food=log(food+.001);
gen log_foodex=log(foodex+.001);
gen log_csmpa=log(csmpa+.001);
gen log_csmpb=log(csmpb+.001);
gen log_csmpc=log(csmpc+.001);
gen log_csmpd=log(csmpd+.001);
gen log_csmpe=log(csmpe+.001);
gen log_csmpf=log(csmpf+.001);

gen log_linc=log(linc+.001);
gen log_hhinc=log(hhinc+.001);
gen log_avgsav=log(avgsav+.001);

gen year1=(year==1);
gen year2=(year==2);
gen year3=(year==3);
gen year4=(year==4);
gen year5=(year==5);

gen city1=(city==1);
gen city2=(city==2);
```

```
gen city3=(city==3);

gen state11=(state==11);
gen state21=(state==21);
gen state22=(state==22);
gen state23=(state==23);
gen state24=(state==24);
gen state25=(state==25);
gen state26=(state==26);
gen state31=(state==31);
gen state32=(state==32);
gen state33=(state==33);
gen state34=(state==34);
gen state35=(state==35);
gen state36=(state==36);
gen state37=(state==37);
gen state38=(state==38);

gen intmo8=(intmo==8);
gen intmo9=(intmo==9);
gen intmo10=(intmo==10);
gen intmo11=(intmo==11);
gen intmo12=(intmo==12);

gen srhlth1=(srhlth==1);
gen srhlth2=(srhlth==2);
gen srhlth3=(srhlth==3);
gen srhlth4=(srhlth==4);
gen srhlth5=(srhlth==5);

gen goodexc=(srhlth==1 | srhlth==2);
*gen educ=(high==1 | coll==1);
gen age_sq=age*age;
gen demt=(cogg==1);
replace demt=. if (cogg==.);

replace smk_term=smk_term/12;
replace alc_term=alc_term/12;

gen smk_age=age-smk_term;
gen alc_age=age-alc_term;

gen early_smk=(smk_age<=19);
gen early_alc=(alc_age<=19);

*replace smk_num=. if (smk_num==100);
replace smk_term=. if (smk_age<=0);
replace alc_term=. if (alc_age<=0);

gen smk_age2=age-(intyr-smk_styr);
gen alc_age2=age-(intyr-alc_styr);

xtset pid year;
save "D:\Research\Smoking_klosa\Data\klosa_cleaned.dta", replace;



*********************************
***** input_husband_wife.do *****
*********************************
#delimit;
set more off;

do "D:\Research\Smoking_klosa\Data\input.do";
sort hhid year;
keep if marr==1;

by hhid: egen gr_female=total(female);
```

```
by hhid: gen temp=_N;

drop if (temp==1 | temp==3 | temp==5 | temp==7 | temp==9);
drop if (temp==2 & gr_female!=1);
drop if (temp==4 & gr_female!=2);
drop if (temp==6 & gr_female!=3);
drop if (temp==8 & gr_female!=4);
drop if (temp==10 & gr_female!=5);
drop if (temp>=11 & temp<=20);

keep if female==0;

foreach v in intyr intmo finr age female lesshigh middle high coll educ marr state county city house nochld
disab exerc srhlth srhlth_r highbp diabete cancr lung liver heart brain psych arthr c_highbp c_diabete c_cancr
c_lung c_liver c_heart c_brain c_psych c_arthr bmi obs csmok psmok nsmok smk_term alc_term drnk smk_num smk_numm
smk_styr alc_styr quityr adl iadl proxy cogg msea mseb msec msed msee msef mseg mseh msei msej msek msel msem
msen mseo msep mseq mser mses grip work empl linc hhinc totnwa totfw avgsav csa csb csc csd cse csf csg csh
lesa lesb lesc les food foodex csmpa csmpb csmpc csmpd csmpe csmpf ortime orplace imrc ser7 dlrc langg visual
epsdc shortm orient cog cog_sm cog_mi ihs_totnwa ihs_totfw log_totnwa log_totfw log_csa log_csg log_food log_foodex
log_csmpa log_csmpb log_csmpc log_csmpd log_csmpe log_csmpf log_linc log_hhinc log_avgsav year1 year2 year3
year4 year5 city1 city2 city3 state11 state21 state22 state23 state24 state25 state26 state31 state32 state33
state34 state35 state36 state37 state38 intmo8 intmo9 intmo10 intmo11 intmo12 srhlth1 srhlth2 srhlth3 srhlth4
srhlth5 goodexc age_sq demt smk_age alc_age early_smk early_alc smk_age2 alc_age2 {;
gen h_‘v’=‘v’;
drop ‘v’;
};
drop pid respid gr_female temp wgta wgtb;
drop if hhid==5994;

save "D:\Research\Smoking_klosa\Data\klosa_husband.dta", replace;
clear all;

do "D:\Research\Smoking_klosa\Data\input.do";
sort hhid year;
keep if marr==1;

by hhid: egen gr_female=total(female);
by hhid: gen temp=_N;

drop if (temp==1 | temp==3 | temp==5 | temp==7 | temp==9);
drop if (temp==2 & gr_female!=1);
drop if (temp==4 & gr_female!=2);
drop if (temp==6 & gr_female!=3);
drop if (temp==8 & gr_female!=4);
drop if (temp==10 & gr_female!=5);
drop if (temp>=11 & temp<=20);

keep if female==1;

foreach v in intyr intmo finr age female lesshigh middle high coll educ marr state county city house nochld
disab exerc srhlth srhlth_r highbp diabete cancr lung liver heart brain psych arthr c_highbp c_diabete c_cancr
c_lung c_liver c_heart c_brain c_psych c_arthr bmi obs csmok psmok nsmok smk_term alc_term drnk smk_num smk_numm
smk_styr alc_styr quityr adl iadl proxy cogg msea mseb msec msed msee msef mseg mseh msei msej msek msel msem
msen mseo msep mseq mser mses grip work empl linc hhinc totnwa totfw avgsav csa csb csc csd cse csf csg csh
lesa lesb lesc les food foodex csmpa csmpb csmpc csmpd csmpe csmpf ortime orplace imrc ser7 dlrc langg visual
epsdc shortm orient cog cog_sm cog_mi ihs_totnwa ihs_totfw log_totnwa log_totfw log_csa log_csg log_food log_foodex
log_csmpa log_csmpb log_csmpc log_csmpd log_csmpe log_csmpf log_linc log_hhinc log_avgsav year1 year2 year3
year4 year5 city1 city2 city3 state11 state21 state22 state23 state24 state25 state26 state31 state32 state33
state34 state35 state36 state37 state38 intmo8 intmo9 intmo10 intmo11 intmo12 srhlth1 srhlth2 srhlth3 srhlth4
srhlth5 goodexc age_sq demt smk_age alc_age early_smk early_alc smk_age2 alc_age2 {;
gen w_‘v’=‘v’;
drop ‘v’;
};
drop pid respid gr_female temp wgta wgtb;
drop if hhid==5994;

save "D:\Research\Smoking_klosa\Data\klosa_wife.dta", replace;
clear all;
```

```
use "D:\Research\Smoking_klosa\Data\klosa_wife.dta", clear;

merge hhid year using "D:\Research\Smoking_klosa\Data\klosa_husband.dta";
drop _merge;
sort hhid year;
by hhid: gen year_an=_n;
save "D:\Research\Smoking_klosa\Data\klosa_husband_wife.dta", replace;

xtset hhid year_an;



*******************************
***** cleaning_table23.do *****
*******************************
#delimit;

foreach v in csmok psmok age marr srhlth c_highbp c_diabete c_heart c_brain c_psych obs exerc drnk empl log_hhinc
log_totnwa year state {;
drop if missing(‘v’);
};

drop if missing(cog);
keep if (age>=45 & age<=75);
drop if cog==0;

by pid: gen temp=_N;
drop if temp==1;
drop temp;

by pid: gen num_cog=_n;



*******************************
***** cleaning_table45.do *****
*******************************
#delimit;

foreach v in w_cog w_csmok w_age w_srhlth w_c_highbp w_c_diabete w_c_heart w_c_brain w_c_psych w_obs w_exerc
w_drnk w_empl w_log_hhinc w_log_totnwa h_cog h_csmok h_age h_srhlth h_c_highbp h_c_diabete h_c_heart h_c_brain
h_c_psych h_obs h_exerc h_drnk h_empl h_log_hhinc h_log_totnwa {;
drop if missing(‘v’);
};

drop if w_cog==0;
drop if h_cog==0;
keep if (w_age>=45 & w_age<=75);
keep if (h_age>=45 & h_age<=75);

drop if (w_csmok==0 & w_psmok==0 & h_csmok==0 & h_psmok==0);
* may differ in unobserved way & may account for assortative mating;

by hhid: gen temp=_N;
drop if temp==1;
drop temp;

by hhid: gen num_cog=_n;



***********************
***** analysis.do *****
***********************
set more off

do "D:\Research\Smoking_klosa\Data\input.do"
```

```
xtset pid year

do "D:\Research\Smoking_klosa\Data\cleaning_table23.do"



***************
*** Table 1 ***
***************
gen smok=.
replace smok=1 if (csmok==0 & psmok==0)
replace smok=2 if (psmok==1)
replace smok=3 if (csmok==1)

gen srhlth_desc=(srhlth==3 | srhlth==4 | srhlth==5)
gen lessmid=(lesshigh==1 | middle==1)
gen nsmok=(psmok==0 & csmok==0)

tabstat ortime orplace imrc dlrc ser7 langg visual epsdc cog_sm cog nsmok psmok csmok age female lessmid high
coll marr srhlth_desc c_highbp c_diabete c_heart c_brain c_psych obs exerc drnk empl, by(smok) save
tabstatmat temp
matrix temp = temp'
mat li temp, noheader

tabstat hhinc totnwa, by(smok) stat(med) save
tabstatmat temp
matrix temp = temp'
mat li temp, noheader

tab smok



***************
*** Table 2 ***
***************
xtreg cog csmok psmok c.age##c.age marr i.srhlth c_highbp c_diabete c_heart c_brain c_psych obs exerc drnk empl
i.year i.state num_cog, fe
outreg2 using D:\Research\Smoking_klosa\Results\table2, dec(3) tex replace
xtreg cog_sm csmok psmok c.age##c.age marr i.srhlth c_highbp c_diabete c_heart c_brain c_psych obs exerc drnk
empl i.year i.state num_cog, fe
outreg2 using D:\Research\Smoking_klosa\Results\table2, dec(3) tex append
xtreg epsdc csmok psmok c.age##c.age marr i.srhlth c_highbp c_diabete c_heart c_brain c_psych obs exerc drnk
empl i.year i.state num_cog, fe
outreg2 using D:\Research\Smoking_klosa\Results\table2, dec(3) tex append

xtreg cog csmok psmok c.age##c.age marr i.srhlth c_highbp c_diabete c_heart c_brain c_psych obs exerc drnk empl
i.year i.state num_cog, fe
estimates store fixed
xtreg cog csmok psmok c.age##c.age marr i.srhlth c_highbp c_diabete c_heart c_brain c_psych obs exerc drnk empl
i.year i.state num_cog, re
estimates store random
hausman fixed random
xtreg cog_sm csmok psmok c.age##c.age marr i.srhlth c_highbp c_diabete c_heart c_brain c_psych obs exerc drnk
empl i.year i.state num_cog, fe
estimates store fixed
xtreg cog_sm csmok psmok c.age##c.age marr i.srhlth c_highbp c_diabete c_heart c_brain c_psych obs exerc drnk
empl i.year i.state num_cog, re
estimates store random
hausman fixed random
xtreg epsdc csmok psmok c.age##c.age marr i.srhlth c_highbp c_diabete c_heart c_brain c_psych obs exerc drnk
empl i.year i.state num_cog, fe
estimates store fixed
xtreg epsdc csmok psmok c.age##c.age marr i.srhlth c_highbp c_diabete c_heart c_brain c_psych obs exerc drnk
empl i.year i.state num_cog, re
estimates store random
hausman fixed random
```

```
***************
*** Table 3 ***
***************

*** Panel A ***
xtreg cog csmok c.age##c.age marr i.srhlth c_highbp c_diabete c_heart c_brain c_psych obs exerc drnk empl i.year
i.state num_cog if (csmok==1 | psmok==1), fe
outreg2 using D:\Research\Smoking_klosa\Results\table3_a, dec(3) tex replace
xtreg cog_sm csmok c.age##c.age marr i.srhlth c_highbp c_diabete c_heart c_brain c_psych obs exerc drnk empl
i.year i.state num_cog if (csmok==1 | psmok==1), fe
outreg2 using D:\Research\Smoking_klosa\Results\table3_a, dec(3) tex append
xtreg epsdc csmok c.age##c.age marr i.srhlth c_highbp c_diabete c_heart c_brain c_psych obs exerc drnk empl
i.year i.state num_cog if (csmok==1 | psmok==1), fe
outreg2 using D:\Research\Smoking_klosa\Results\table3_a, dec(3) tex append

*** Panel B ***
gen vascular=(c_highbp==1 | c_diabete==1 | c_heart==1 | c_brain==1)
xtreg cog i.csmok##i.vascular c.age##c.age marr i.srhlth c_psych obs exerc drnk empl i.year i.state num_cog if
(csmok==1 | psmok==1), fe
outreg2 using D:\Research\Smoking_klosa\Results\table3_b, dec(3) tex replace
xtreg cog_sm i.csmok##i.vascular c.age##c.age marr i.srhlth c_psych obs exerc drnk empl i.year i.state num_cog
if (csmok==1 | psmok==1), fe
outreg2 using D:\Research\Smoking_klosa\Results\table3_b, dec(3) tex append
xtreg epsdc i.csmok##i.vascular c.age##c.age marr i.srhlth c_psych obs exerc drnk empl i.year i.state num_cog
if (csmok==1 | psmok==1), fe
outreg2 using D:\Research\Smoking_klosa\Results\table3_b, dec(3) tex append

*** Panel C ***
*gen smk_num_gr=.
*replace smk_num_gr=1 if (smk_num>=1 & smk_num<=10)
*replace smk_num_gr=2 if (smk_num>=11 & smk_num<=20)
*replace smk_num_gr=3 if (smk_num>=21)

gen smk_int=(smk_num/20)*smk_term if (csmok==1)
replace smk_int=(smk_numm/20)*smk_term if (psmok==1)
xtile smk_num_dec = smk_int, nq(10)
gen smk_num_gr=.
replace smk_num_gr=1 if (smk_num_dec>=1 & smk_num_dec<=3)
replace smk_num_gr=2 if (smk_num_dec>=4 & smk_num_dec<=6)
replace smk_num_gr=3 if (smk_num_dec>=7 & smk_num_dec<=8)
replace smk_num_gr=4 if (smk_num_dec>=9 & smk_num_dec<=10)

xtreg cog ib1.smk_num_gr c.age##c.age marr i.srhlth c_highbp c_diabete c_heart c_brain c_psych obs exerc drnk
empl i.year i.state num_cog if (csmok==1 | psmok==1), fe
outreg2 using D:\Research\Smoking_klosa\Results\table3_c, dec(3) tex replace
xtreg cog_sm ib1.smk_num_gr c.age##c.age marr i.srhlth c_highbp c_diabete c_heart c_brain c_psych obs exerc
drnk empl i.year i.state num_cog if (csmok==1 | psmok==1), fe
outreg2 using D:\Research\Smoking_klosa\Results\table3_c, dec(3) tex append
xtreg epsdc ib1.smk_num_gr c.age##c.age marr i.srhlth c_highbp c_diabete c_heart c_brain c_psych obs exerc drnk
empl i.year i.state num_cog if (csmok==1 | psmok==1), fe
outreg2 using D:\Research\Smoking_klosa\Results\table3_c, dec(3) tex append


***************
*** Table 4 ***
***************
*do "D:\Research\Smoking_klosa\Data\input_husband_wife.do"
use "D:\Research\Smoking_klosa\Data\klosa_husband_wife.dta", clear
xtset hhid year_an

do "D:\Research\Smoking_klosa\Data\cleaning_table45.do"

local husb "c.h_age##c.h_age i.h_srhlth h_c_highbp h_c_diabete h_c_heart h_c_brain h_c_psych h_obs h_exerc h_drnk
h_empl"
local wife "c.w_age##c.w_age i.w_srhlth w_c_highbp w_c_diabete w_c_heart w_c_brain w_c_psych w_obs w_exerc w_drnk
w_empl"
```

```
xtreg w_cog w_csmok h_csmok `wife' `husb' i.year i.w_state num_cog, fe robust
outreg2 using D:\Research\Smoking_klosa\Results\table4, dec(3) tex replace
xtreg w_cog w_csmok h_csmok `wife' `husb' i.year i.w_state num_cog if (w_csmok==0), fe robust
outreg2 using D:\Research\Smoking_klosa\Results\table4, dec(3) tex append

gen ncs_cog=.
replace ncs_cog=h_cog if (h_csmok==0 & w_csmok==1)
replace ncs_cog=w_cog if (h_csmok==1 & w_csmok==0)
replace ncs_cog=w_cog if (h_csmok==0 & w_csmok==0)
*Input missing values if (h_csmok==1 & w_csmok==1)

replace w_age=h_age if (h_csmok==0 & w_csmok==1)
replace w_srhlth=h_srhlth if (h_csmok==0 & w_csmok==1)
replace w_c_highbp=h_c_highbp if (h_csmok==0 & w_csmok==1)
replace w_c_diabete=h_c_diabete if (h_csmok==0 & w_csmok==1)
replace w_c_heart=h_c_heart if (h_csmok==0 & w_csmok==1)
replace w_c_brain=h_c_brain if (h_csmok==0 & w_csmok==1)
replace w_c_psych=h_c_psych if (h_csmok==0 & w_csmok==1)
replace w_obs=h_obs if (h_csmok==0 & w_csmok==1)
replace w_exerc=h_exerc if (h_csmok==0 & w_csmok==1)
replace w_drnk=h_drnk if (h_csmok==0 & w_csmok==1)
replace w_empl=h_empl if (h_csmok==0 & w_csmok==1)
replace w_state=h_state if (h_csmok==0 & w_csmok==1)

gen hh_csmok=.
replace hh_csmok=(h_csmok==1 | w_csmok==1)

xtreg ncs_cog hh_csmok `wife' `husb' i.year i.w_state num_cog, fe robust
outreg2 using D:\Research\Smoking_klosa\Results\table4, dec(3) tex append

xtreg w_cog w_csmok h_csmok `wife' `husb' i.year i.w_state num_cog, fe
estimates store fixed
xtreg w_cog w_csmok h_csmok `wife' `husb' i.year i.w_state num_cog, re
estimates store random
hausman fixed random
xtreg w_cog w_csmok h_csmok `wife' `husb' i.year i.w_state num_cog if (w_csmok==0), fe
estimates store fixed
xtreg w_cog w_csmok h_csmok `wife' `husb' i.year i.w_state num_cog if (w_csmok==0), re
estimates store random
hausman fixed random
xtreg ncs_cog hh_csmok `wife' `husb' i.year i.w_state num_cog, fe
estimates store fixed
xtreg ncs_cog hh_csmok `wife' `husb' i.year i.w_state num_cog, re
estimates store random
hausman fixed random


***************
*** Table 5 ***
***************

*** Panel A ***
use "D:\Research\Smoking_klosa\Data\klosa_husband_wife.dta", clear
xtset hhid year_an

do "D:\Research\Smoking_klosa\Data\cleaning_table45.do"

local husb "c.h_age##c.h_age i.h_srhlth h_c_highbp h_c_diabete h_c_heart h_c_brain h_c_psych h_obs h_exerc h_drnk
h_empl"
local wife "c.w_age##c.w_age i.w_srhlth w_c_highbp w_c_diabete w_c_heart w_c_brain w_c_psych w_obs w_exerc w_drnk
w_empl"

xtreg w_cog w_csmok h_csmok `wife' `husb' w_log_hhinc w_log_totnwa i.year i.w_state num_cog, fe robust
outreg2 using D:\Research\Smoking_klosa\Results\table5_a, dec(3) tex replace
xtreg w_cog w_csmok h_csmok `wife' `husb' w_log_hhinc w_log_totnwa i.year i.w_state num_cog if (w_csmok==0),
fe robust
outreg2 using D:\Research\Smoking_klosa\Results\table5_a, dec(3) tex append
```

```
gen ncs_cog=.
replace ncs_cog=h_cog if (h_csmok==0 & w_csmok==1)
replace ncs_cog=w_cog if (h_csmok==1 & w_csmok==0)
replace ncs_cog=w_cog if (h_csmok==0 & w_csmok==0)
*Input missing values if (h_csmok==1 & w_csmok==1)

replace w_age=h_age if (h_csmok==0 & w_csmok==1)
replace w_srhlth=h_srhlth if (h_csmok==0 & w_csmok==1)
replace w_c_highbp=h_c_highbp if (h_csmok==0 & w_csmok==1)
replace w_c_diabete=h_c_diabete if (h_csmok==0 & w_csmok==1)
replace w_c_heart=h_c_heart if (h_csmok==0 & w_csmok==1)
replace w_c_brain=h_c_brain if (h_csmok==0 & w_csmok==1)
replace w_c_psych=h_c_psych if (h_csmok==0 & w_csmok==1)
replace w_obs=h_obs if (h_csmok==0 & w_csmok==1)
replace w_exerc=h_exerc if (h_csmok==0 & w_csmok==1)
replace w_drnk=h_drnk if (h_csmok==0 & w_csmok==1)
replace w_empl=h_empl if (h_csmok==0 & w_csmok==1)
replace w_state=h_state if (h_csmok==0 & w_csmok==1)

gen hh_csmok=.
replace hh_csmok=(h_csmok==1 | w_csmok==1)

xtreg ncs_cog hh_csmok ‘wife’ ‘husb’ w_log_hhinc w_log_totnwa i.year i.w_state num_cog, fe robust
outreg2 using D:\Research\Smoking_klosa\Results\table5_a, dec(3) tex append

*** Panel B ***
use "D:\Research\Smoking_klosa\Data\klosa_husband_wife.dta", clear
xtset hhid year_an

do "D:\Research\Smoking_klosa\Data\cleaning_table45.do"

local husb "c.h_age##c.h_age i.h_srhlth h_c_highbp h_c_diabete h_c_heart h_c_brain h_c_psych h_obs h_exerc h_drnk
h_empl"
local wife "c.w_age##c.w_age i.w_srhlth w_c_highbp w_c_diabete w_c_heart w_c_brain w_c_psych w_obs w_exerc w_drnk
w_empl"

gen temp=((h_quityr<=2) & (w_srhlth==1 | w_srhlth==2))
by hhid: egen temp_tot=mean(temp)
keep if temp_tot==0

xtreg w_cog w_csmok h_csmok ‘wife’ ‘husb’ i.year i.w_state num_cog, fe robust
outreg2 using D:\Research\Smoking_klosa\Results\table5_b, dec(3) tex replace
xtreg w_cog w_csmok h_csmok ‘wife’ ‘husb’ i.year i.w_state num_cog if (w_csmok==0), fe robust
outreg2 using D:\Research\Smoking_klosa\Results\table5_b, dec(3) tex append

gen ncs_cog=.
replace ncs_cog=h_cog if (h_csmok==0 & w_csmok==1)
replace ncs_cog=w_cog if (h_csmok==1 & w_csmok==0)
replace ncs_cog=w_cog if (h_csmok==0 & w_csmok==0)
*Input missing values if (h_csmok==1 & w_csmok==1)

replace w_age=h_age if (h_csmok==0 & w_csmok==1)
replace w_srhlth=h_srhlth if (h_csmok==0 & w_csmok==1)
replace w_c_highbp=h_c_highbp if (h_csmok==0 & w_csmok==1)
replace w_c_diabete=h_c_diabete if (h_csmok==0 & w_csmok==1)
replace w_c_heart=h_c_heart if (h_csmok==0 & w_csmok==1)
replace w_c_brain=h_c_brain if (h_csmok==0 & w_csmok==1)
replace w_c_psych=h_c_psych if (h_csmok==0 & w_csmok==1)
replace w_obs=h_obs if (h_csmok==0 & w_csmok==1)
replace w_exerc=h_exerc if (h_csmok==0 & w_csmok==1)
replace w_drnk=h_drnk if (h_csmok==0 & w_csmok==1)
replace w_empl=h_empl if (h_csmok==0 & w_csmok==1)
replace w_state=h_state if (h_csmok==0 & w_csmok==1)

gen hh_csmok=.
replace hh_csmok=(h_csmok==1 | w_csmok==1)
```

```
xtreg ncs_cog hh_csmok ‘wife’ ‘husb’ i.year i.w_state num_cog, fe robust
outreg2 using D:\Research\Smoking_klosa\Results\table5_b, dec(3) tex append

*** Panel C ***
use "D:\Research\Smoking_klosa\Data\klosa_husband_wife.dta", clear
xtset hhid year_an

do "D:\Research\Smoking_klosa\Data\cleaning_table45.do"

local husb "c.h_age##c.h_age i.h_srhlth h_c_highbp h_c_diabete h_c_heart h_c_brain h_c_psych h_obs h_exerc h_drnk
h_empl"
local wife "c.w_age##c.w_age i.w_srhlth w_c_highbp w_c_diabete w_c_heart w_c_brain w_c_psych w_obs w_exerc w_drnk
w_empl"

gen temp=((h_quityr<=2) & (w_highbp==1 | w_diabete==1 | w_heart==1 | w_brain==1))
by hhid: egen temp_tot=mean(temp)
keep if temp_tot==0

xtreg w_cog w_csmok h_csmok ‘wife’ ‘husb’ i.year i.w_state num_cog, fe robust
outreg2 using D:\Research\Smoking_klosa\Results\table5_c, dec(3) tex replace
xtreg w_cog w_csmok h_csmok ‘wife’ ‘husb’ i.year i.w_state num_cog if (w_csmok==0), fe robust
outreg2 using D:\Research\Smoking_klosa\Results\table5_c, dec(3) tex append

gen ncs_cog=.
replace ncs_cog=h_cog if (h_csmok==0 & w_csmok==1)
replace ncs_cog=w_cog if (h_csmok==1 & w_csmok==0)
replace ncs_cog=w_cog if (h_csmok==0 & w_csmok==0)
*Input missing values if (h_csmok==1 & w_csmok==1)

replace w_age=h_age if (h_csmok==0 & w_csmok==1)
replace w_srhlth=h_srhlth if (h_csmok==0 & w_csmok==1)
replace w_c_highbp=h_c_highbp if (h_csmok==0 & w_csmok==1)
replace w_c_diabete=h_c_diabete if (h_csmok==0 & w_csmok==1)
replace w_c_heart=h_c_heart if (h_csmok==0 & w_csmok==1)
replace w_c_brain=h_c_brain if (h_csmok==0 & w_csmok==1)
replace w_c_psych=h_c_psych if (h_csmok==0 & w_csmok==1)
replace w_obs=h_obs if (h_csmok==0 & w_csmok==1)
replace w_exerc=h_exerc if (h_csmok==0 & w_csmok==1)
replace w_drnk=h_drnk if (h_csmok==0 & w_csmok==1)
replace w_empl=h_empl if (h_csmok==0 & w_csmok==1)
replace w_state=h_state if (h_csmok==0 & w_csmok==1)

gen hh_csmok=.
replace hh_csmok=(h_csmok==1 | w_csmok==1)

xtreg ncs_cog hh_csmok ‘wife’ ‘husb’ i.year i.w_state num_cog, fe robust
outreg2 using D:\Research\Smoking_klosa\Results\table5_c, dec(3) tex append


***************
*** Table 6 ***
***************
use "D:\Research\Smoking_klosa\Data\klosa_husband_wife.dta", clear
xtset hhid year_an

do "D:\Research\Smoking_klosa\Data\cleaning_table45.do"

local husb "c.h_age##c.h_age i.h_srhlth h_c_highbp h_c_diabete h_c_heart h_c_brain h_c_psych h_obs h_exerc h_drnk
h_empl"
local wife "c.w_age##c.w_age i.w_srhlth w_c_highbp w_c_diabete w_c_heart w_c_brain w_c_psych w_obs w_exerc w_drnk
w_empl"

sum w_cog if (w_csmok==0), detail
di 26.72255-3.599991
di 26.72255-(1.5*3.599991)
di 26.72255-(2*3.599991)

gen cut1=(w_cog<=23.122559)
```

```
gen cut2=(w_cog<=21.322563)
gen cut3=(w_cog<=19.522568)

xtreg cut1 w_csmok h_csmok `wife' `husb' i.year i.w_state num_cog if (w_csmok==0), fe robust
outreg2 using D:\Research\Smoking_klosa\Results\table6, dec(3) tex replace
xtreg cut2 w_csmok h_csmok `wife' `husb' i.year i.w_state num_cog if (w_csmok==0), fe robust
outreg2 using D:\Research\Smoking_klosa\Results\table6, dec(3) tex append
xtreg cut3 w_csmok h_csmok `wife' `husb' i.year i.w_state num_cog if (w_csmok==0), fe robust
outreg2 using D:\Research\Smoking_klosa\Results\table6, dec(3) tex append
```