Title: Heckman-Selection or Two-Part models for alcohol studies? Depends.

Authors
Reka Sundaram-Stukel, PhD
Research Fellow
University of Wisconsin-Madison
Department of Economics
Madison, Wisconsin 53703

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Key statement
The currently underused Heckman estimation model is contextually appropriate for modelling problem drinking as compared to the two-part model. Exclusion restrictions in the Heckman model can be justified contextually to survey conditions, questions asked, and model design.

Abstract
Aims: To re-introduce the Heckman model as a valid empirical technique in alcohol studies.
Design: To estimate the determinants of problem drinking using a Heckman and a two-part estimation model. Psychological and neuro-scientific studies justify my underlying estimation assumptions and covariate exclusion restrictions. Higher order tests checking for multicollinearity validate the use of Heckman over the use of two-part estimation models. I discuss the generalizability of the two models in applied research.
Settings and Participants: Two pooled national population surveys from 2016 and 2017 were used: the Behavioral Risk Factor Surveillance Survey (BRFS), and the National Survey of Drug Use and Health (NSDUH).
Measurements: Participation in problem drinking and meeting the criteria for problem drinking.
Findings: Both U.S. national surveys perform well with the Heckman model and pass all higher order tests. The Heckman model corrects for selection bias and reveals the direction of bias, where the two-part model does not. For example, the coefficients on age are upward biased and unemployment is downward biased in the two-part where the Heckman model does not have a selection bias. Covariate exclusion restrictions are sensitive to survey conditions and are contextually generalizable.
Conclusions: The Heckman model can be used for alcohol (smoking studies as well) if the underlying estimation specification passes higher order tests for multicollinearity and the exclusion restrictions are justified with integrity for the data used. Its use is merit-worthy because it corrects for and reveals the direction and the magnitude of selection bias where the two-part does not.
Introduction

Alcohol and smoking studies have a subtle preference of choosing two-part models over Heckman models. The origins of this can be traced to a seminal paper by Madden (2008)[1]. While he stresses that this preference should be evaluated contextually on data availability and model specification, in practice, a certitude has settled in and the Heckman model has lost favor in addiction studies. Many published articles by accomplished empiricists post-2008 chose the two-part model and rejected the Heckman model[2-8]. An economics literature search revealed over 100 economic articles were published using Heckman selection model in the last two years and an equal number using a two-part model. However, since 2008 its use in alcohol or smoking studies die out.

The purpose of this article is to dispel the confusion surrounding the usage of a Heckman model and make it easier to base modeling choice on things that matter: research question, data availability, and correcting biases in estimation. The central sources of confusion about the Heckman model come from four sources[1, 5-9]. First, when there are no defensible exclusion restrictions, is the two-part model better than a Heckman? Second, how can we ascertain that the covariates are not multicollinear with the inverse Mills ratio (IMR)? And, is it easy to implement in practice? Third, scientific researchers are frustrated because a disproportionate number of research papers get rejected since reviewers are taught to be extremely skeptical of exclusion restrictions and experimental studies in economics have made their use highly unpopular. And finally, why should a researcher add additional analysis by choosing a Heckman model if estimating a two-part model side steps all these concerns?

I approached answering these questions very practically, relying only on: data constraints, estimation of both the two-part and the Heckman model, testing, and excluding a theoretical exposition of the two methods. I found that model specification and choice of exclusion restrictions are data dependent. Tests for multicollinearity are standard in statistical packages and easy to use. The Heckman estimation passes all test for multicollinearity for both datasets used in this paper and is internally valid within each dataset. I found that the coefficients from the two-part and the Heckman models are similar in signs but differ in magnitudes for some variables. This conveys key information. The Heckman model is important
because it gives us unbiased estimates and informs us of the magnitude of bias. My results also show that not all effects are the same across the datasets because question framing and administering give rise to procedural biases that are difficult to correct. Whether or not to impose an uncorrelated error structure or ignore selection bias is typically determined by the research question of interest and data availability[5-9]. Where instruments or exclusion restrictions are not available, a two-part model will provide estimates, however, a zero inflated Poisson (ZIP) estimation method would be sophisticated analysis for many alcohol or smoking related questions[10]. In populations surveys many respondents are not at risk for addiction this gives rise to a lot of zero responses. I argue that the first line of modeling choice should directly address participation in at-risk behavior therefore making ZIP or Heckman more suitable. Furthermore, eliminating the use of a Heckman model on the basis of one study restricts the modeling choices available to researchers without merit.

Materials and Methods
I used the 2017 and 2018 cross-sections of two annual national population surveys, the Behavioral Risk Factor Surveillance Survey (BRFS) and the National Survey on Drug Use and Health (NSDUH), to test the use of the Heckman and two-part models. BRFS is a not a national survey in the strictest sense of the sampling language[11]. It is a standardized state specific survey with the core and discretionary questions administered by each individual state. Assembled together, the states form a quazi-national population sample of 921,688 American respondents ages 18 and over. NSDUH is a nationally representative population survey where state level data is restricted to prevent identification[12]. I limited the NSDUH sample to 85,179 respondents ages 18+ to keep it consistent with BRFS ages. Because of this difference between surveys, the BRFS estimates are not directly comparable to the NSDUH estimates for alcohol use. Finally, I used data from the National Institute of Alcohol Abuse and Alcoholism to track state alcohol policies[13-17].

Definition of Problem Drinking
For this analysis, problem drinking is defined as anyone at-risk for binge- or heavy- drinking. Three key alcohol questions in BRFS help partially identify a problem drinking sub-sample and the in-depth
questions in NSDUH about alcohol-use and -misuse help fully identify the problem drinking sub-sample. BRFS defines binge drinking as males (females) consuming five (four) or more drinks on one occasion in the past 30 days and heavy drinking as adult males (females) having more than fourteen (seven) drinks per week. NSDUH defines heavy drinking as five (four) or more drinks on the same occasion for males (females) on five or more consecutive days in the past 30 days (eTable3). Note that in NSDUH, the criteria for heavy drinking also includes binge drinking. These definitions of problem drinking give rise to ambiguity and procedural bias which contextually influence modelling choices, estimations, and interpretations[11-17]. Reporting results from both data sources allows us to examine how exclusion restrictions can be tailored to survey specifications and test the appropriate use of a Heckman model.

Problem drinking takes on the value 1 if the respondent meets the criteria of heavy- or binge-drinking as described above or takes the value 0 otherwise. Problem drinking frequency, a measure of acuteness, is the number of occasions a respondent binge- or heavy- drinks in a 30-day period. Problem drinking intensity, a measure of severity, is the number of alcohol drinks consumed on one occasion in a 30-day period. The quantity of problem drinking simply equals frequency multiplied by intensity over the 30-day period\(^a\).

**Statistical Methods**

I explain my estimation strategy by breaking it down into two stages even though it is estimated jointly using full information maximum likelihood. Stage 1 investigates the factors influencing the decision to participate in problem drinking. Since only 20% of the respondents fit the criteria for problem drinking, there exists a selection problem to start with. Stage 2 uses the selection correction in the estimation. I estimated both dataset using the Heckman and the two-part modelling approach. The Heckman model used a correction from the participation equation called the inverse Mills ratio (IMR). IMR when used as an explanatory variable in the second stage, can create multi-collinearity problems; thus, validating the Heckman model requires passing two tests. For a Heckman estimation model to be free of

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\(^a\) Clinicians use a seven-day period to calculate quantity whilst this analysis uses a 30-day period.
multicollinearity problems it needs to score less than 10 on a first order test of a variance inflation factor (VIF) and less than 100 on a second order condition number (CN) test (mathematical details in annexed supplement).

Both Heckman selection and Two-Part models involve joint estimation of two equations: participation in problem drinking and frequency (or intensity) of problem drinking—they are estimated jointly using full information maximum likelihood. The modelling assumptions between the two differ. The Two-Part model assumes the errors between the participation and frequency (or intensity) equations are uncorrelated, whereas the Heckman model assumes they are correlated. Secondly, the Two-Part model does not require exclusion restrictions while the Heckman model does\(^b\)[18].

**Variables used in estimation**

The estimation of participation, frequency, and intensity of alcohol consumption use socio-economic status (SES), health, and behavioral variables as independent covariates. Four key indicators link SES and problem drinking behavior—education, income, labor status, and access to healthcare. Also included are two calculated variables (poor health and co-morbid risky behaviors) and two sources of stress (health-stress and marital-stress—cTable4).

**Exclusion Restrictions**

Table 1 presents the justification of the exclusion of covariates from the participation, frequency, and intensity equations—these are called exclusion restrictions. First, it is important to recognize this analysis is correlational not causal. There is only one causal relationship and that is intensity (quantity of drinks per occasion) and frequency (number of drinking occasions) of problem drinking are jointly determined conditional on problem drinking (Figure 1\(^{[19]}\) Panel C gives the causal diagram). In this paper, I focus on the decision to participate in problem drinking and I treat intensity and frequency as two separate reduced form estimations. Doing this allows me to illustrate how correcting for selection alters signs or

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\(^b\) Strictly speaking the Heckman model is identified without exclusion restrictions if “shape” restrictions are used.
magnitudes for the covariates of interest. I do not include the causal estimation of intensity and frequency in this analysis.

Figure 1 breaks down the selection problem in two stages and illustrates the determinants of two separate questions. In stage 1 (Figure 1 Panel A), I ask the question: What are the correlates of problem drinking? Note that by drawing out a correlational model, I can easily separate out covariates that belong in each stages of the estimation. In stage 2 (Figure 1 Panel B), I ask: What are the correlates of the frequency and intensity of drinking alcohol conditional on fitting the problem drinking criteria? By incorporating a selection correction, I do not need to consider frequency or intensity decision for non-problem drinkers. As Table 1 shows the exclusion restrictions, restriction 1 comes from clinical studies, it uses insights from neurosciences which argue that improper risk-taking behavior comes from impairments in executive functioning which control impulsivity (see eTable 2 for neuroscience). A person with impairments in executive functioning is more likely to engage in multiple risky-behaviors and has a lower threshold for problem drinking. For this reason, comorbid risky-behaviors appear in the participation model only. In Figure 1, this corresponds to CT → RB → PD which is a visual representation of the argument offered above.

Restriction 2 corrects for the state alcohol climate by incorporating state specific alcohol policies for the BRFS sample (in Figure 1 ARP → PD, Table 1, eTable 2, eTable 5). The policies free beverages, multiple servings at one time, multiple servings for one price, and various happy hour restrictions take on the value 1 if a state has it in effect and 0 if otherwise. Together these state policies affect participation estimation only because typically, these alcohol policies are aimed at restricting problem drinking in bars and not at-home alcohol consumption. We do not need to include state dummies because state policies capture the intended effects. Similarly, the NSDUH workplace alcohol policy variables belong in participation estimation because these variables depend on workers’ awareness of consequences of drinking to employment (Figure 1 ARP → PD, Table 1, eTable 6). Six questions in the NSDUH survey characterise a workplace policies on alcohol and drugs these are: written policies, coverage of alcohol and
drugs, provision of educational materials on alcohol and drugs, provision of employee assistance, testing of employees at hiring, and awareness of consequences of alcohol and drug misuse.

The SES variables are also estimation dependent. Restriction 3 includes employment in the frequency and participation equations but not in the intensity equation because employment status is deeply tied to socializing and networking after work hours. While these opportunities increase frequency, they do not necessarily increase intensity—peer effects could also deter intensive drinking. Restriction 4 excludes income from the frequency but includes it in the intensity equation because you need more money to drink more units of alcohol. In the NSDUH frequency estimation, I include aggression—responses to several under the influence questions that I have classified as self-harm or other-harm—because they are symptomatic of impaired executive functioning and observed conditional on frequent participation in problem drinking (Figure 1 Panel B AB→F, eTable6). Table 1 lists the justifications for all the economic assumptions underlying the exclusion restrictions (see also Figure 1 Panels A, B and C for a graph).

The models, tests, and results were calculated using Stata in November 2019 – May 2021.

Results

A summary of variables for both data are available in the annexed supplement (eTable 7-8). The participation results for both two-part or Heckman estimation model remain the same. In the spirit of this paper, I restrict our attention to how survey design affects the participation results. Table 3 shows that the magnitudes for both BRFS and NSDUH samples are fairly well aligned for most variables. However, the sign and magnitude of the SES variables of employment and income vary across the two. After correcting for state fixed policy effects in BRFS, employment increases problem drinking by 2% and unemployment decreases problem drinking by 6% (Table2). Using NSDUH data, I found that the respondents who were employed problem drink less by 3% and the respondents who were unemployed problem drink more by 6%, however, these results do not correct for state fixed effects. The second significant difference comes from observing how state alcohol restrictions (e.g. restrictions on free drinks and volume discount) deter problem drinking.
As described earlier, the Heckman model incorporates the inverse mills ratio (IMR) to correct for sample selection in the second stage. The IMR could generate a multi-collinearity problem and so two tests are typically done. The first order test regresses the IMR on the rest of the covariates and then calculates the variance inflation factor (VIF)\textsuperscript{[26-28]}. If the VIF $\leq 10$ then the model is said to be estimable without concerns over multicollinearity. The second order test involves calculating the condition number (CN). If $CN < 100$ then multicollinearity is not a problem; if $CN \geq 100$ then the model has serious multicollinearity problems\textsuperscript{[27-28]}. Table 3 shows that the variance inflation factor (VIF) for all models estimated using BRFS and NSDUH data. All models show a VIF $< 10$ (less than 5 is best) and a VIF on IMR $< 10$, and models 3 and 4 have a VIF on IMR $< 5$. This means all the models across both datasets pass the VIF test. This is in stark contrast to Madden’s 2008 study where they found that the IMR regressed on covariates had a VIF score of greater than 100 thus failing the first order multicollinearity test. In this analysis, the CN for all estimated models using BRFS and NSDUH data were less than 10, which means my model specifications do not pose a multicollinearity problem. Maddens’s study also failed the second order tests with CN score in the 133 to 400 range for their estimated models. Thus, Madden’s rejection of the Heckman model, though valid in his study for female smoking and alcohol consumption, does not generalize its use in other alcohol (or smoking) studies using different survey data.

There are several reasons for this. First, Madden’s study had a really small sample of 359/1259 respondents who were smokers and 879/1259 who were alcohol consumers, our data has over 97K alcohol consumers for BRFS, and over 23K for NSDUH sample (we do not include respondents who smoke in our study but BRFS and NSDUH sample sizes are large enough to generalize to the smoking context as well). Second, his choice of covariates may not support the multicollinearity test, for example, the number respondents in widowed, and divorced/separated are too small to be treated as separate categories and could ill condition the covariance matrix. Third, his main source of concern VIF over age and age squared. It is not clear that age squared is good regressand in alcohol studies. Age performs better as discrete categories because life style and health matter in alcohol consumption. Madden’s study does not account for health in his estimation model. This leads me to the conclusion Madden’s model suffered
from a mis-specification bias in addition to having too small a sample to support his analysis. I do not pursue a true model test using BRFS and NSDUH data because I pass both the first and second order tests.

Once the selection-correction variable IMR passes the multicollinearity test, it can be used as a regressand in the second stage equation (intensity or frequency) with a correlated error structure, thus correcting for selection bias. I estimated the two-part model with exclusion restrictions even though they are not necessary to keep it comparable with the Heckman models. I also estimated a short regression Heckman model with no exclusion restrictions to check the VIF and CN under those conditions and found that overall the Heckman model passes that test too: the VIF on IMR frequency equation is 21 but the mean VIF is less than 5 (see eTable 9). Though strictly not needed the Heckman model may perform better if estimated with exclusion restrictions, however, if reasonable exclusion restrictions are not available it can be estimated using shape restrictions\textsuperscript{[18]}. Table 4 presents the results for the intensity estimation and Table 5 presents the results for the frequency estimation.

The reader should note that many of the variables in the Heckman and two-part model show the same signs and magnitudes. If the results are significantly different from the two-part models I bring attention to it and discuss it. In addition, the differences between the Heckman and two-part models are more pronounced with the BRFS data than the NSDUH data. I offer two explanations for this: first the BRFS data corrects for state fixed effects and the NSDUH data doesn’t because it is nationally representative; and second, the BRFS data is a larger sample as compared to the NSDUH data. I will return to the differences in the dataset as needed.

Focusing on the BRFS intensity equation results (Table 4), I found that although the two models agree in signs, being female results in 8% lowered intensity of problem drinking using BRFS the Heckman model than the two-part estimation. Compared to age 65+, for age group 50 – 69 and age group 18 – 49 the magnitude of coefficients are significantly lower in the Heckman model than two-part estimation. Income effects are also significant after correcting for sample selection. For NSDUH, correcting for selection bias results in a higher statistical significance of the results. Awareness of
workplace consequences of intensely drinking decrease intensity by 3%, but not significantly so (Table 4, NSDUH).

The frequency of alcohol consumption results (Table 5) are similar to those above, there is a magnitude difference between the Heckman and two-part, where females are 3% increased frequency to problem drink after correcting for selection bias in BRFS. The age effects show that the two-part results are upward biased, unemployment is downward biased, and income is upward biased. There are no sign reversals in this model design. For NSDUH frequency estimation in both the Heckman and the two-part models result in almost results identical illustrating that correcting for selection bias doesn’t yield any additional benefit. I elaborate on this issue in the discussion section.

**Discussion and Conclusion**

Puzzled by Madden’s 2008 paper results and widespread acceptance of it in alcohol and smoking studies I started with the hypothesis that the Heckman model could be sensitive to the data generating process. My first finding is that survey design adds layers of distortion in interpreting results. For example, looking at participation equation results on employment, NSDUH and BRFS contradict each other. Further investigation points to three problems: one, definitions of variables across surveys (eTable 3-6); two, nuances in employment status; and three, state fixed effects. I argue that the BRFS results on employment are generalizable, because some states have drinking prohibitions that are likely to distort results of the NSDUH sample. Neither survey can shed light on the subtle nuances of how employment and unemployment states affect problem drinking. For example, those who are out of the labor-force (and not seeking employment) may use alcohol to self-medicate depression and those seeking employment may use alcohol to network for employment-related connections. The underlined data generating process does not focus on unpacking how unemployment affects drinking behavior. Collecting data on duration of unemployment, job-search activities, mental health, and social support, for example, could help us tease out some of the effects of unemployment on alcohol consumption.

In this analysis, I exclude state and many workplace policy variables from intensity and frequency estimations. One could argue these exclusions create an artificial modeling environment, that
should use experimental or instrumental techniques instead. However, looking closely, I found state restrictions on volume drinking yield a modest 1% decrease in participation and workplace policies do not seem to have the intended decline in participation (Table 3) thus, it not clear that either state alcohol restrictions or workplace alcohol policies affect frequency or intensity of drinking beyond participatory effects. Note, a statistically significant 9% decrease comes from awareness of workplace policies on alcohol, not the policies themselves (Table 3). It is this finding of significance in awareness that gives policy makers a concrete direction. If both estimations were not juxtaposed, we would miss it. Investments in alcohol education could be the key policy tool for addressing problem drinking.

Experimental studies on the brain basis of addiction inform these exclusion restrictions for risky behaviors—the studies find those who engage in risky-behaviors may have impairments in executive functioning. Engaging in one risky-behavior increases the probability of engaging in another. So, I included other risky-behaviors in the estimation of the probability of problem drinking (participation equation). Once we correct for selection bias, comorbid risky behaviors need not enter the intensity and frequency estimations. Because conditional on problem drinking, we want to answer a new question what else do we see that influences frequency and intensity of problem drinking? This sometimes becomes a sticky-wicket with reviewers—how do we know for sure something can be excluded? The answer is quite simple. Impairments in reward seeking brain networks facilitate problem drinking, once in the problem drinking group, other factors influence alcohol consumption intensity or frequency such as affordability, age, education, and health. Put differently, if these networks in the brain had an inhibitory response, then a person would be less likely to engage in problem drinking; it is the excitatory response that opens the door to problem drinking. Once the door is opened, the question becomes what other factors facilitate problem drinking? We are no longer interested in the factors that mediate the decision to problem drink.

Is the correction for selection bias really needed if two-part models perform as well as Heckman models? My results show this is dependent on the survey design. If I am estimating using NSDUH data, then I can get away with two-part model and can make reasonable generalizations, though, we have seen employment effects cannot be generalized. A researcher may not be privy to differences between BRFS
and NSDUH. NSDUH should be viewed as the nation’s pulse in diagnosing alcohol and drug behavior, whereas BRFS allows us to plunge into state specific effects of alcohol -use or -misuse. Controlling for state fixed effects and correcting for selection bias gives us more accurate results both in terms of signs and magnitudes which then can be generalized to the population of interest. As we have seen, some results are upward biased and some results are downward biased. If we were sure all variables would be biased in one direction we could get away with estimating a two-part model and admitting to nature of bias.

Estimating a Heckman model does not imply significant time costs in testing for multicollinearity. It is no more tedious than conducting a Wald test or a F-test—I used standard STATA commands to estimate and run diagnostic tests, SPSS also has these tests as part of their routine drop down menu, and R has these tests built in as part of model fitting diagnostics. None of these models significantly increased computational time. Thus, estimation and tests are not a barrier for estimating Heckman models. Why am I, as an economist, fighting for the retention of the Heckman model in alcohol and smoking studies? Recall, I argued that there is only one causal relationship which is frequency and intensity are jointly determined. Because the amount of alcohol a person consumes is subject to an income constraint we can infer shadow prices of alcohol. To make a statement beyond how education and employment are correlated with the frequency and intensity of drinking, an economist needs to correct for selection bias. For example, a correlational analysis showed that work-place awareness of alcohol policies act as deterrents to alcohol consumption, and being employed increased frequency of problem drinking, but not intensity. A causal analysis of frequency and intensity will deepen our understanding on how employment, education, and income can inform policies for a safer society. I take this up in a different paper.

Summing up, this paper contributes by recommending meaningful use of partial identification in public health and dispelling the need for incredible certitude—where we expect model exclusion restrictions to be robust beyond available data or identifiable beyond the limits of observational data available[32-33]. We continue to learn from observational population studies in meaningful ways. To this
end, the Heckman model works well with alcohol and smoking studies. If estimating a selection model is not feasible then, a zero inflated Poisson model (ZIP) is superior to the two-part alternative, unless errors are clearly uncorrelated, because it allows the researcher to directly account for the over dispersion in zero responses\textsuperscript{[10,34]}. In these surveys, problem drinking is equal to zero for nearly 80\% of the sampled respondents. We do not take this up here seriously but in terms of modelling alcohol or smoking decisions the ZIP models and Heckman models should be considered first over two-part models.
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Figure 1. Models of problem drinking with frequency and intensity of drinking.

Panel A: Stage 1 of Heckman-Selection Problem Drinking (yes, no)

- PD - problem drinking
- I - number of drinks per episode of drinking
- F - number of episodes of drinking 30 day
- CT - Clinical Trials Results
- RB - Risky Behaviors
- CT -> RB is the brain basis of engaging in co-morbid risky behaviors
- ARP - State or workplace alcohol policies
- X - vector of covariates that affect PD
- X_F - vector of covariates that affect F
- X_I - vector of covariates that affect I
- AB - Alcohol related harmful behavior
- IMR - selection correction

Panel B: Stage 2 of Heckman-Selection Frequency or Intensity conditional on PD=1

Panel C: A Causal Estimation of Frequency and Intensity conditional on PD=1
Table 1: Covariate Exclusion Restrictions for Estimated Models

| Covariates                  | P | F | I | Justification                                                                                                                                                                                                 |
|-----------------------------|---|---|---|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Co-morbid Risky Behavior    | Y | N | N | **Restriction 1**: These combined effects feed into each other and strengthen the case that risky behaviours disproportionately affect participation in PD. A person participating in problem drinking is likely to have one or more co-morbid risky habits such as smoking, poor eating habits, improper seat-belt use, and/or driving under the influence. Because substance use and engagement in risky behaviour trigger reward seeking and reduce sensitivity to the pleasure associated with the substance (or behavior), we would expect to see increased alcohol (behaviour) consumption for the same level of rewards. Consumption also heightens the activation of the brain’s stress system potentially compromising executive control, increasing impulsivity, and impairing decision making. |
| State Alcohol Policies NIAAA| Y | N | N | **Restriction 2 BRFS only**: BRFS is a state level data set we used state policies and restrictions in our participation equation. This is easily justified since problem drinking happens in the absence of restrictions. On the other hand, state level restrictions on happy hours, number of free drinks, or volume discount deter or minimize participation. We couldn’t use this for NSDUH because state level data was not available for public use. |
| Workplace policies NSDUH    | Y | N | Y | **Restriction 2 NSDUH only**: The NSDUH data set has a detailed section devoted to workplace polices for drug or alcohol-use and -misuse. We used awareness of workplace alcohol policies in the participation equation because these are largely intended to deter participation in drinking. We include alcohol testing and consequences in the intensity equation. They are, however, excluded from the frequency equation because frequent problem drinking results in behavioural patterns of self- and other- harm and definitively ignores consequences of problem drinking. |
| Employment                  | Y | Y | N | **Restriction 3**: Employment does not appear in the intensity equation. The reason for this is because employment status potentially generates opportunities for engaging in PD but may not affect the intensity with which one engages in a given episode of drinking. |
| Income                      | Y | N | Y | **Restriction 4**: Income does not affect frequency of problem drinking because to drink intensively needs income.                                                                                                                                                                                                 |

Source: Own calculations
NSDUH – National Survey of Drug Use and Health
BRFS – Behavioral Risk Factor Surveillance System
ER- Exclusion Restriction
P = Participation equation; I = Intensity equation; F = Frequency equation
Y = Included in equation; N = Not included in equation

We thank an anonymous referee for pointing out that exclusion restrictions needed to be provided in a clear precise format. We thank an anonymous referee for pointing out that workplace policies may plausibly affect intensity of drinking. We argue that problem drinking is a prerequisite for the intensity argument which asks “by how much are you problem drinking?” So, workplace policies act predominantly as a deterrent to problem drinking. Similarly, state policies can plausibly enter the frequency or intensity calculations but do not probably get there before.
| Variables                        | BRFS<sup>a</sup> probit | dydx  | NSDUH<sup>b</sup> Probit | dydx  |
|---------------------------------|------------------------|-------|--------------------------|-------|
| **Dependent Variable Problem Drinker 1 = Yes; 0 = No** |            |       |                          |       |
| Female                          | -0.224***              | -0.049*** | -0.264***                | -0.080*** |
|                                 | (0.004)                | (0.001)  | (0.025)                  | (0.008)  |
| **Age<sup>c</sup>**            |            |       |                          |       |
| 18 - 49 years old               | 0.613***              | 0.134*** | 0.608***                 | 0.186*** |
|                                 | (0.006)                | (0.001)  | (0.004)                  | (0.002)  |
| 50 - 64 years old               | 0.295***              | 0.065*** | 0.316***                 | 0.096*** |
|                                 | (0.006)                | (0.001)  | (0.015)                  | (0.005)  |
| **Socio-Economic Status<sup>d</sup>** |            |       |                          |       |
| Employed                        | 0.109***              | 0.024*** | -0.112**                 | -0.034** |
|                                 | (0.005)                | (0.001)  | (0.048)                  | (0.015)  |
| Part time Employment            | 0.038***              | 0.008*** | -0.190***                | -0.058*** |
|                                 | (0.010)                | (0.002)  | (0.049)                  | (0.015)  |
| Unemployed                      | -0.275***             | -0.060*** | 0.188***                 | 0.057*** |
|                                 | (0.009)                | (0.002)  | (0.030)                  | (0.009)  |
| Income $ 0 - $ 50,000           | -0.101***             | -0.022*** | -0.002                   | -0.002   |
|                                 | (0.005)                | (0.001)  | (0.007)                  | (0.007)  |
| Income > 75,000                 | 0.076***              | 0.017*** | 0.005                    | 0.005   |
|                                 | (0.005)                | (0.001)  | (0.007)                  | (0.007)  |
| **Health Stressors**            |            |       |                          |       |
| One Health Stressor             | -0.161***             | -0.035*** | -0.045                   | -0.014   |
|                                 | (0.030)                | (0.006)  | (0.030)                  | (0.009)  |
| Two Health Stressor             | 0.157***              | 0.034*** | -0.237**                 | -0.072*** |
|                                 | (0.028)                | (0.006)  | (0.028)                  | (0.009)  |
| Three Health Stressors          | 0.125***              | 0.027*** | -0.226**                 | -0.069*** |
|                                 | (0.029)                | (0.006)  | (0.076)                  | (0.023)  |
| Risky-Behavior                 | 0.186***              | 0.041*** | -0.001                  |         |
|                                 | (0.003)                | (0.001)  | (0.004)                  |         |
| **State Policy Variables for BRFS** | -0.046***             | -0.010*** | 1.037***                 | 0.317*** |
| Free Drinks                     | (0.005)                | (0.001)  | (0.188)                  | (0.056)  |
| Multiple Servings               | -0.020***             | -0.004*** | -0.001***                | -0.000*** |
|                                 | (0.007)                | (0.002)  | (0.000)                  | (0.000)  |
| Single Serving Discount         | 0.043***              | 0.009*** | -0.002***                | -0.001*** |
|                                 | (0.005)                | (0.001)  | (0.000)                  | (0.000)  |
| Happy Hour Restrictions         | -0.008                | -0.002   | -0.002**                 | -0.001*** |
|                                 | (0.007)                | (0.001)  | (0.000)                  | (0.000)  |
| Unlimited Fixed Drinks          | 0.010*               | 0.002*   | 0.148***                 | 0.045*** |
|                                 | (0.006)                | (0.001)  | (0.025)                  | (0.008)  |
| Volume Discount                 | -0.066***             | -0.014*** | -0.244***                | -0.075*** |

<sup>a</sup> Estimated on the BRFS sample

<sup>b</sup> Estimated on the NSDUH sample

<sup>c</sup> Reference category: 50 - 64 years old

<sup>d</sup> Reference category: No Health Stressor

Table 2: Participation in Problem Drinking Equation Estimation for Pooled 2016-2017
Problem drinking is defined as binge or heavy drinking in the last 30 days.

Reference categories:  
165 years or older, 2Unable to work, 3$50,000 – $74,999
Table 3: Summary of Collinearity Diagnosis for all Four Models

| 2nd Stage Models | Variance Inflation Factor (\(^\text{cVIF}\)) of j covariates\(^3\) | (\(^\text{cVIF}\)) | Condition Number\(^4\) |
|------------------|-------------------------------------------------|------------------|------------------------|
| Model 1: BRFS\(^a\) | VIF-IMR\(_{Fj}\) | 6.68 | 8.73 |
| Frequency\(^1\) equation | Mean VIF-\(X_{i|F\_adj}\) | 2.42 | |
| Model 2: BRFS\(^a\) | VIF-IMR\(_{ij}\) | 5.14 | 5.61 |
| Intensity\(^2\) equation | Mean VIF-\(X_{i|I\_adj}\) | 2.25 | |
| Model 3: NSDUH\(^b\) | VIF-IMR\(_{Fj}\) | 4.38 | 5.87 |
| Frequency\(^3\) equation | Mean VIF-\(X_{i|F\_adj}\) | 2.23 | |
| Model 4: NSDUH\(^b\) | VIF-IMR\(_{ij}\) | 4.95 | 6.08 |
| Intensity\(^2\) equation | Mean VIF-\(X_{i|I\_adj}\) | 2.23 | |

Source: Own calculations.
\(^a\)BRFS–Behavioral Risk Factor Surveillance System 2016-2017
\(^b\)NSDUH–National Survey of Drug Use and Health 2016-2017

\(^1\)Frequency measures the number of times a respondent binge or heavy drinks in a 30-day period.

\(^2\)Intensity measures the number of alcohol drinks consumed on one occasion in a 30-day period.

\(^3\)VIF-IMR (I, F) are the variance inflation factor on the variable IMR when regressed on the rest of the \(X_i\)'s in the frequency and intensity of problem drinking models.

The collinearity diagnostic tables for each covariate X-VIF\(_{i|F}\) is available upon request.

\(^4\)The condition number is based on the maximum and minimum Eigen values of the root matrix \(X'X\)

In practice, a condition number <100 means there is no significant source of multicollinearity in the model. For values between 100 and 1000 there is danger of multicollinearity and the model is potentially mis-specified, one or more variables are collinear with the rest. A value greater than 1000 means there is systemic multicollinearity and the model is mis-specified.
Table 4: Intensity Estimation using BRFS\textsuperscript{a} and NSDUH\textsuperscript{b} 2016-2017

| Dependent Variable | Ln Intensity\textsuperscript{2} | BRFS | NSDUH |
|--------------------|----------------------------------|------|-------|
|                    | Heckman | Two-Part | Heckman | Two-Part |
| Constant           | 2.261*** | 1.446*** | 0.853*** | 0.931*** |
|                    | (0.045)  | (0.021)  | (0.091)  | (0.115)  |
| Frequency\textsuperscript{1} | 0.234*** | 0.238*** | 0.283*** | 0.283*** |
|                    | (0.003)  | (0.003)  | (0.002)  | (0.001)  |
| Female             | -0.255*** | -0.337*** | -0.219*** | -0.209*** |
|                    | (0.009)  | (0.008)  | (0.015)  | (0.005)  |
| Age\textsuperscript{3} | 0.159*** | 0.391*** | 0.310*** | 0.279**  |
| 18 - 49 years old  | (0.017)  | (0.008)  | (0.056)  | (0.029)  |
| 50 - 64 years old  | 0.053*** | 0.179*** | 0.157*** | 0.138**  |
|                    | (0.013)  | (0.009)  | (0.028)  | (0.015)  |
| Race               | -0.015   | 0.001    | -0.042** | -0.042   |
| White              | (0.016)  | (0.016)  | (0.018)  | (0.017)  |
| Black              | -0.203*** | -0.199*** | -0.224*** | -0.224*** |
|                    | (0.019)  | (0.018)  | (0.017)  | (0.017)  |
| AIAN               | -0.006   | -0.008   | 0.223*** | 0.224*   |
|                    | (0.028)  | (0.027)  | (0.061)  | (0.062)  |
| Asian              | -0.062** | -0.099*** | -0.096*** | -0.095*** |
|                    | (0.031)  | (0.024)  | (0.005)  | (0.005)  |
| Socio-Economic Variables\textsuperscript{4,6} | 0.081*** | -0.001 | 0.026*** | 0.027*** |
| Income $0 - $50,000\$ | (0.014) | (0.012) | (0.005) | (0.004) |
| Income > $75,000   | -0.037*** | 0.002  | -0.039*** | -0.041   |
|                    | (0.013)  | (0.010)  | (0.013)  | (0.015)  |
| Less than High School | 0.030    | 0.016    | -0.033   | -0.033   |
|                    | (0.025)  | (0.026)  | (0.063)  | (0.063)  |
| Some College or Technical College | -0.022** | -0.023** | -0.067 | -0.067 |
|                    | (0.009)  | (0.010)  | (0.068)  | (0.068)  |
| Graduated College Technical College | -0.052*** | -0.057*** | -0.230*** | -0.230* |
|                    | (0.007)  | (0.007)  | (0.076)  | (0.077)  |
| Market Access      | 0.006    | 0.012**  |         |         |
|                    | (0.005)  | (0.006)  |         |         |
| Marital Stress     | -0.002   | 0.001    |         |         |
|                    | (0.008)  | (0.008)  |         |         |
| Health Variables   | 0.003*** | 0.003*** | -0.026*** | -0.025   |
| Mental Health (BRFS) | (0.000) | (0.000) | (0.009) | (0.009) |
|                    | 0.020**  | 0.019**  | -0.007   | -0.008   |
|                          |    |    |     |     |
|--------------------------|----|----|-----|-----|
|                          | 0.008 | 0.008 | 0.014 | 0.015 |
| Alcohol Test (NSDUH)     |     |     | 0.050*** | 0.044*** |
|                          |     |     | (0.004) | (0.004) |
| Alcohol Consequence (NSDUH) | -0.035 | -0.030 |     |     |
|                          |     |     | (0.022) | (0.017) |
| Observations             | 97,182 | 97,182 | 23,864 | 23,864 |

Source: Own calculations.

*aBRFS–Behavioral Risk Factor Surveillance System 2016-2017.

bNSDUH–National Survey of Drug Use and Health 2016-2017.

**Frequency** measures the number of times a respondent binge or heavy drinks in a 30-day period.

**Intensity** measures the number of alcohol drinks consumed on one occasion in a 30-day period. Clustered standard errors in parentheses

***p < 0.01, **p < 0.05, *p < 0.1;

Reference categories: 365 years or older, 4unable to work, 5Income $50,000–$74, 999, 6High school
Table 5: Frequency Estimation using BRFS and NSDUH 2016-2017

| Dependent Variable | Log Frequency\(^1\) |  |  |  |  |
|--------------------|---------------------|---|---|---|---|
|                    | BRFS                | NSDUH |                     |                     |                     |
|                    | Heckman Two-Part    | Heckman Two-part |
| Covariates         |                     |                     |                     |                     |
| Constant           | -0.401*** (0.066)   | 0.587*** (0.042)   | -0.696*** (0.053)   | 0.293** (0.060)   |
| Intensity\(^2\)    | 0.919*** (0.024)    | 0.520*** (0.016)   | 0.925*** (0.024)    | 0.521*** (0.016)   |
| Female             | 0.120*** (0.019)    | -0.031 (0.021)     | 0.094*** (0.017)    | -0.064 (0.024)     |
| Age\(^3\)          |                     |                     |                     |                     |
| 18 –49 years old   | -0.361*** (0.027)   | -0.243*** (0.021)  | -0.294*** (0.022)   | -0.153** (0.027)   |
| 50 –64 years old   | -0.124*** (0.028)   | -0.146*** (0.040)  | -0.089*** (0.026)   | -0.096 (0.039)     |
| Race               |                     |                     |                     |                     |
| White              | 0.026 (0.034)       | 0.214*** (0.020)   | 0.027 (0.034)       | 0.214*** (0.020)   |
| Black              | 0.172*** (0.045)    | 0.138*** (0.010)   | 0.177*** (0.043)    | 0.138*** (0.010)   |
| AIAN               | 0.130*** (0.048)    | -0.009 (0.092)     | 0.135*** (0.048)    | -0.011 (0.093)     |
| Asian              | 0.026 (0.053)       | -0.053*** (0.014)  | 0.015 (0.054)       | -0.050* (0.014)    |
| Socio-Economic Status\(^4\) |                     |                     |                     |                     |
| Employed           | -0.011 (0.010)      | -0.007 (0.007)     | 0.004 (0.010)       | 0.033* (0.008)     |
| Part-time          | 0.005 (0.023)       | 0.007 (0.016)      | 0.008 (0.023)       | 0.038 (0.016)      |
| Unemployed         | 0.112*** (0.030)    | -0.017 (0.013)     | 0.083** (0.033)     | 0.015 (0.015)      |
| Income $0 –$50,000| 0.029* (0.017)      | 0.017 (0.013)      | 0.06 (0.016)        | 0.017 (0.014)      |
| Income > $75,000   | -0.051*** (0.017)   | 0.012 (0.009)      | -0.039** (0.017)    | 0.018 (0.007)      |
| Market Access      | 0.059*** (0.012)    |                     | 0.061*** (0.012)    |                     |
| Stress (BRFS)      | 0.073*** (0.022)    | 0.084*** (0.018)   | 0.075*** (0.022)    | 0.083** (0.019)    |
|                      |                     | 0.327*** (0.027)   |                      | 0.329*** (0.027)   |
|                      |                     | 0.312*** (0.050)   |                      | 0.320** (0.052)    |
| Stress & Alcohol Related Aggression (NSDUH) |                     |                     |                     |                     |
| Marital Stress     | 0.006*** (0.001)    | 0.016 (0.015)      | 0.007*** (0.001)    | 0.017 (0.015)      |
| Life time Diagnosis| 0.000 (0.017)       | -0.044*** (0.008)  | 0.002 (0.018)       | -0.044** (0.008)   |
| Observations       | 96,923              | 96,923             | 23,864              | 23,864             |

Source: Own calculations BRFS and NSDUH 2016-2017.

BRFS\(^a\) – Behavioral Risk Factor Surveillance System

NSDUH\(^b\) – National Survey of Drug Use and Health
Frequency\(^1\) measures the number of times a respondent binge or heavy drinks in a 30-day period.  
Intensity\(^2\) measures the number of alcohol drinks consumed on one occasion in a 30-day period.  
Means are weighted by population weights.  
Robust (NSDUH) and clustered standard errors (BRFS) in parentheses.  
\(* * * p < 0.01, ** p < 0.05, * p < 0.1\)  
Reference categories 3 65 years or older, 4 unable to work, 7 Income $50,000 –$74,999, 6 High school
eTable 1: Select literature review of two-part model and Heckman-selection model articles

| Study and Year | Dependent Variables | Models | Statistically Significant Results | Data |
|----------------|---------------------|--------|-----------------------------------|------|
| 1. Leung S. F., Yu S. 1996 | Methods paper comparison of methods using simulated variables | FIML, NTPM, DTPM, Tests | There is a model specificity bias against HSM, Condition number better predictor of collinearity. | Simulated Data 1996 |
| 2. Mullahy J. 1998 | Methods Paper, Doctor visits | Logit, TPM, ECM, MTPM | Main results are: MTPM > ECM > OLS > TPM. The choice is application specific and one must take into consideration bias and robustness. | Health Interview Survey 1992 |
| 3. Berggren F. and Sutton M. 1999 | Participation, Frequency and Intensity | Selection model with first stage Probit and second stage 2SLS estimated separately | Age effects and income Effects. Model performs well no tests conducted. | Malömd Health Survey 1994, Sweden |
| 4. Madden D. 2008 | Alcohol (and smoking) participation and consumption level | HSM and TPM | Main result: for this specification TPM is preferred over HSM because their model failed variance inflation test. Becomes gold standard in alcohol literature to use TPM. | Saffron Survey 1998, Dublin |

Source: Own review
HSM: Heckman Model; TPM: Two-part model; MTPM-modified TPM; NTPM-nonlinear TPM; ECM: Exponential conditional mean; FIML: Full information maximum likelihood
1. Leung S. F., Yu S. On the Choice between sample selection and Two-Part models. Journal of Econometrics 1996; Vol 72:1-2: 197-229. https://doi.org/10.1016/0304-4076(94)01720-4
2. Mullahy J. Much ado about two: reconsidering retransformation and the two-part model in health econometrics 1998; Vol 17:3 247-281.
3. Berggren F., Sutton M. Are frequency and intensity of participation decision bearing aspects of consumption? An analysis of drinking behavior. Applied Economics 1999; Vol 31: pp865-874. https://doi.org/10.1080/000368499323823.
4. Madden D. Sample selection versus two-part models revisited: The case of female smoking and drinking. Journal of Health Economics 2008; Vol 27-2: 300-307.https://doi.org/10.1016/j.jhealeco.2007.07.001
| Study, Journal and Year | Style of Paper | Brain Basis | Findings and Assumptions |
|-------------------------|----------------|-------------|--------------------------|
| 1. Goldstein R. and Volkov N. in American Journal of Psychiatry 2002 | Conceptual and evidence | orbitofrontal cortex, anterior cingulate gyrus, limbic system and frontal cortical area | 1-RISA addiction stages are drug administration, drug craving, compulsive drug administration and drug withdrawal. **Conclusion:** addiction connotes cortically regulated cognitive and emotional processes which overvalues drug related rewards, downplays natural rewards and decreases inhibitory control for drugs. **ER:** participation equation. |
| 2. Koob G. Le Moal M. in Commentary in Nature and Neuroscience 2005 | Commentary | nucleus accumbens, MDA in VT, orbitofrontal, medial prefrontal, prelimbic/cingulate and extended amygdala | The dark side of addiction is characterized by decreased normal motivational systems or decreased enjoyment of natural rewards and increased activation of anti-reward systems drives substance abuse and not a hyperactive or sensitized reward state for the substance per se. **Assumption:** other co-morbid risky-behaviors compromise increases in normal motivational systems. |
| 3. Koob G. and Volkov N. In Neuropsychopharmacology 2010 | Conceptual model and evidence | mesolimbic dopamine system, ventral striatal pallidal thallic loops, dorsal striatum, pre-frontal systems, and extended amygdala | Addiction has stages: binge and intoxication, withdrawal and negative affect and preoccupation and anticipation. Bottom line addiction leads to impulsivity/compulsivity and loss of executive control—this progression is subtle and can have lasting effects on the brain circuitry thus increasing vulnerability to dysregulation initially or long into abstinence. **Conclusion:** participation in other risky-behaviors are co-occurring with participation in problem drinking. |
| 4. Angolia A. E. and Herman H. A. in Alcohol 2018 | Conceptual Paper with evidence | amygdala, intra-amygdala microcircuits and amygdalar subnuclei | Engagement of CRF circuitry by alcohol could alter amygdala activity particularly areas associated with anxiety and stress, and conversely these areas could be activated by stress potentially alter their sensitivity to the effects of alcohol. **Assumption:** Alcohol exhibits cyclical behavior with stress and anxiety and thus desensitizing ability to exercise restraint leading to addiction. |

Source: Own review
CRF: Corticotropin releasing factor; MDA: mesocorticolimbic dopamine system;
VT: ventral tegmental; I-RISA: impaired response inhibition and salience attribution.
ER: Exclusion Restriction

1. Goldstein, R. Z., and Volkow, N. D. Drug addiction and its underlying neurobiological basis: Neuroimaging evidence for the involvement of the frontal cortex. American Journal of Psychiatry 2002; 159(10), 1642-1652.
2. Koob, G. F., and Le Moal, M. Plasticity of reward neurocircuitry and the ‘dark side’ of drug addiction. Nature Neuroscience, 2019; 8(11), 1442-1444.
3. Koob, G. F., and Volkow, N. D. Neurocircuitry of addiction. Neuropsychopharmacology, 2019; 35(1), 217–238.
4. Agoglia, A., Herman, M. The Center of the Emotional Universe: alcohol, stress, and CRF1 amygdala circuitry. Alcohol 2018; doi: 10.1016/j.alcohol.2018.03.009.
### eTable 3: Alcohol Questions BRFS and NSDUH 2016-2017

| Dependent Variables | Alcohol Questions | BRFS 2016-2017 | NSDUH 2016-2017 |
|---------------------|-------------------|-----------------|-----------------|
| Alcohol Ever        | Have you ever had a drink of an alcoholic beverage? | n/a              | N = 36,606       |
| Alcohol Try         | Age when first drank alcohol                          | n/a              | N = 36,211       |
| Alcohol Days        | Number days had one or more drinks in past 30 days?   | N = 237,677      | N = 24,013       |
| Problem Drinking    | PD status 30 days                                      | N = 59,205       | N = 13,039       |
| Problem Drinking Frequency | Number occasions had four/five or more drinks past 30 days? | N = 59,205       | N = 13,039       |
| Problem Drinking Intensity | Usual number of drinks per day past 30 days?         | N = 59,2054      | N = 22,908       |

**Co-Morbid Risky Behavior Questions**

|                          | Question                                      | Yes | Yes |
|--------------------------|-----------------------------------------------|-----|-----|
| Seat-Belt Use            | Wear a seat-belt when you drive                | Yes | Yes |
| At-risk Smoking          | Risk Smoking one or more packs                 | Yes | Yes |
| At-risk BMI              | at risk for being overweight or obese          | Yes | No  |
| Risk Taker               | Like to test yourself by taking risks          | No  | Yes |

Source: NSDUH 2016-2017. BRFS 2016-2017.
| Variable        | Explanation                                                                                                                                 |
|-----------------|--------------------------------------------------------------------------------------------------------------------------------------------|
| Market-Access   | Market access was constructed through factor analysis using five factor variables: unemployment, low income, low education, no access to doctor, and no access to health care. For NSDUH we use health insurance as measure of market access. |
| Poor Health     | Poor health is equal to one if respondents report being in fair or poor health at the time of survey.                                      |
| Risky-Behavior  | Risky behavior was calculated as the sum of all co-occurring risky behaviors which include seat-belt use, at-risk smoking, at-risk BMI, and risk taking. |
| Aggression      | The NSDUH data allowed us to construct a measure for alcohol related aggression using responses to specific questions regarding displays of aggression post alcohol consumption: We create two variables Self-Harm and Other-harm see eTable3. |
| Health-Stress   | Health-stress were equal to the sum of a positive responses to having diabetes, heart disease, stroke, cancer, asthma, hypertension, obesity, arthritis, or kidney diseases and took on the value 4 if the respondents had more than three chronic conditions. |
| Marital Stress  | Marital stress was equal to 1 if a person was divorced or separated at the time of interview and 0 otherwise.                               |

Source: NSDUH 2016-2017. BRFS 2016-2017.
| Type of Restrictions | Description |
|----------------------|-------------|
| Free Beverages       | A check-mark appears in the Free Beverages column if the State prohibits on-premises retailers from providing free alcoholic beverages to patrons either as a promotional practice or on a case-by-case basis (e.g., on a birthday or anniversary, as compensation for poor service, etc.). |
| Multiple Servings at One Time | A check-mark appears in the Multiple Servings at One Time column if the State prohibits on-premises retailers from serving a customer more than one drink at a time without regard to price, as in the retail practice of “lining up” drinks in front of a customer whether or not he/she is paying full price for each drink. Two different alcoholic beverages served at the same time to a single customer, if such “drink” is a customary combination (such as a shot of spirituous liquor with a malt beverage), is considered one drink. |
| Multiple Servings for a Single Serving Price | A check-mark appears in the Multiple Servings for a Single Serving Price column if the State prohibits on-premises retailers from serving a customer multiple servings for a single price (e.g. two-for-one, three-for-one, etc.). |
| Happy Hours–Reduced Price | |
| Banned               | State prohibits offering a discount or price promotion to customers during any subset of normal hours of operation (such as reduced prices during “Happy Hours”). States that ban price promotions during a subset of business hours may allow promotions that last for a full business day (Full Day Price Reductions – see Definitions). Such States are coded as “banned” by APIS. |
| Restricted           | State allows on-premises establishments to offer a discount or price promotion to customers but there are restrictions or limitations as to the hours or days the specials may be offered. |
| None–No law exists prohibiting happy hours. | For States that allow on-premises discounts or price promotions but with restrictions to a subset of business hours, this column indicates the days and/or times during which such discounts or promotions are permitted. For States that ban on premises discounts or price promotions for a subset of business hours, this column indicates those that do not ban such promotions if offered for a full business day (Full Day Price Reductions). |
| Unlimited Beverages for a Fixed Price or Period | A check-mark appears in the Unlimited Beverages for a Fixed Price or Period column if the state prohibits the price promotion practice of allowing patrons to receive an unlimited number of alcoholic drinks for a fixed price or during a fixed period of time (e.g., all-you-can-drink, beat-the-clock, etc.). |
| Increased Volume without Increase in Price | A checkmark appears in the Increased Volume without Increase in Price column if the state prohibits offering drinks with increased amounts of alcohol at the same price as regular-sized drinks (e.g., double shots for the price of single shots). |

Source: NIAAA.
eTable 6: Work Alcohol Policy and Aggression Variables in NSDUH 2016-2017

| Work Alcohol Policy Questions | Q1 | At your workplace, is there a written policy about employee use of alcohol or drugs? |
|-------------------------------|----|-----------------------------------------------------------------------------------|
|                               | Q2 | Does this policy cover only alcohol, only drugs, or both alcohol and drugs?        |
|                               | Q3 | At your workplace, have you ever been given any educational information regarding the use of alcohol or drugs? |
|                               | Q4 | Through your workplace, is there access to any type of employee assistance program or other type counseling program for employees who have alcohol or drug-related problems? |
|                               | Q5 | Does your workplace ever test its employees for alcohol use? Random or at hire. |
|                               | Q6 | Awareness of consequences to alcohol use at work |

| Aggression Questions | Q1 | Did you continue to drink alcohol even though you thought drinking was causing you to have problems with your emotions, nerves, or mental health? |
|---------------------|----|-----------------------------------------------------------------------------------------------------------------------------------|
|                     | Q2 | Did you continue to drink alcohol even though you thought drinking was causing you to have physical problems?                      |
|                     | Q3 | During the past 12 months, did you regularly drink alcohol and then do something where being drunk might have put you in physical danger? |
|                     | Q4 | During the past 12 months, did drinking alcohol cause you to do things that repeatedly got you in trouble with the law?            |
|                     | Q5 | Did you continue to drink alcohol even though you thought your drinking caused problems with family or friends?                   |

| Other-Harm | Q6 | During the past 12 months, did drinking alcohol cause you to have serious problems like this either at work, home (child neglect) |
|------------|----|-----------------------------------------------------------------------------------------------------------------------------|
|            | Q7 | In the past 12 months, were you arrested and booked for drunkenness or other liquor law violations?                            |
|            | Q8 | In the past 12 months, were you arrested and booked for driving under the influence of alcohol or drugs?                     |

Source: NSDUH 2016-2017.
### Table 7: Summary of Key Variables BRFS 2016-2017

| Variable                      | Prevalence | Frequency | Intensity |
|-------------------------------|------------|-----------|-----------|
| Problem Drinkers              | 0.17       | 4.39 [4.36, 4.43] | 7.35 [7.32, 7.38] |
| **Sex**                       |            |           |           |
| Female                        | 0.12       | 3.54 [3.49, 3.59] | 5.57 [5.54, 5.60] |
| Male                          | 0.22       | 4.89 [4.84, 4.94] | 8.40 [8.36, 8.44] |
| **Age**                       |            |           |           |
| 18 to 49 years old            | 0.22       | 4.01 [3.97, 4.05] | 7.58 [4.76, 4.85] |
| 50 to 64 years old            | 0.14       | 4.49 [4.42, 4.57] | 6.07 [7.54, 7.62] |
| 65 or older                   | 0.07       | 3.76 [3.67, 3.86] | 4.81 [6.02, 6.11] |
| **Education**                 |            |           |           |
| Less than High School         | 0.13       | 5.93 [5.72, 6.13] | 8.63 [8.45, 8.81] |
| High School                   | 0.16       | 5.08 [5.00, 5.17] | 7.90 [7.84, 7.97] |
| Some College or Technical College | 0.18   | 4.26 [4.20, 4.33] | 7.27 [7.22, 7.32] |
| Graduated College Technical College | 0.18 | 3.34 [3.29, 3.38] | 6.50 [6.47, 6.54] |
| **Employment**                |            |           |           |
| Employed                      | 0.22       | 4.27 [4.23, 4.31] | 7.48 [7.44, 7.51] |
| Unemployed                    | 0.17       | 5.17 [4.98, 5.35] | 7.99 [7.83, 8.16] |
| Unable to work                | 0.09       | 6.57 [6.30, 6.83] | 7.81 [7.60, 8.01] |
| Out of Labor force            | 0.11       | 4.19 [4.11, 4.27] | 6.48 [6.43, 6.53] |
| **Income**                    |            |           |           |
| Income $0 − $50,000 Income   | 0.16       | 4.5 [4.03, 4.20] | 7.28 [7.23, 7.33] |
| $50,000 − $75,000 Income >   | 0.19       | 4.11 [4.45, 4.56] | 7.08 [7.02, 7.15] |
| $75,000                       | 0.22       | 3.67 [3.63, 3.73] | 6.84 [6.80, 6.88] |
| **Race**                      |            |           |           |
| White                         | 0.18       | 3.92 [3.85, 4.00] | 7.29 [7.23, 7.36] |
| Black                         | 0.13       | 3.84 [3.79, 3.89] | 7.06 [7.02, 7.10] |
| AIAN                          | 0.17       | 4.59 [4.53, 4.66] | 7.38 [7.33, 7.43] |
| Asian                         | 0.1        | 5.58 [5.44, 5.73] | 7.88 [7.77, 7.99] |
| Other                         | 0.18       | 8.35 [7.99, 8.71] | 9.39 [9.06, 9.73] |
| **Health Stressors**          |            |           |           |
| None                          | 0.14       | 3.6 [3.14, 4.05] | 6.00 [5.52, 6.48] |
| One health problem            | 0.09       | 4.25 [4.07, 4.43] | 6.96 [6.80, 7.12] |
| Two health problems           | 0.19       | 4.26 [4.22, 4.30] | 7.41 [7.38, 7.44] |
| Three or more health problems | 0.12       | 5.09 [4.99, 5.18] | 7.16 [7.09, 7.23] |
| Poor health                   | 0.16       | 4.07 [4.01, 4.15] | 7.15 [7.08, 7.21] |
| Lifetime Depression           | 0.18       | 4.85 [4.76, 4.94] | 7.30 [7.23, 7.37] |
| **Comorbid Risk Factors**     |            |           |           |
| Smoking                       | 0.29       | 6.22 [6.13, 6.31] | 8.72 [8.65, 8.80] |
| High BMI                      | 0.17       | 4.42 [4.38, 4.47] | 7.52 [7.48, 7.56] |
| No Seat Belt                  | 0.25       | 5.35 [5.26, 5.45] | 8.67 [8.59, 8.75] |
| Marital Stress                | 0.16       | 5.55 [5.44, 5.67] | 8.67 [8.59, 8.75] |

| State                         | Prevalence | Frequency | Intensity |
|-------------------------------|------------|-----------|-----------|
| National Median               | 0.17       | 4.456     | 7.385     |
| Alabama                       | 0.13       | 4.33 [4.01, 4.64] | 7.468 [7.09, 7.84] |
| Alaska                        | 0.19       | 4.45 [4.04, 4.86] | 7.425 [7.15, 7.70] |
| Arizona                       | 0.15       | 4.32 [4.08, 4.57] | 7.351 [7.16, 7.54] |
| State           | Value | Lower Bound | Upper Bound | Confidence Interval |
|-----------------|-------|-------------|-------------|---------------------|
| Arkansas        | 0.15  | 5.42        | 5.98        | 9.167 [8.55, 9.78]  |
| California      | 0.17  | 3.99        | 4.20        | 7.048 [6.88, 7.22]  |
| Colorado        | 0.19  | 4.01        | 4.21        | 7.096 [6.95, 7.24]  |
| Connecticut     | 0.16  | 3.68        | 3.89        | 6.891 [6.69, 7.09]  |
| Delaware        | 0.16  | 4.66        | 5.10        | 7.385 [6.94, 7.83]  |
| District of Columbia | 0.26 | 3.75 | 4.04 | 6.312 [6.11, 6.52]  |
| Florida         | 0.15  | 4.75        | 4.92        | 7.298 [7.18, 7.42]  |
| Georgia         | 0.13  | 4.60        | 5.01        | 7.189 [6.90, 7.48]  |
| Hawaii          | 0.19  | 4.85        | 5.11        | 8.34 [8.08, 8.59]   |
| Idaho           | 0.16  | 4.87        | 5.28        | 7.80 [7.46, 8.13]   |
| Illinois        | 0.20  | 4.01        | 4.27        | 7.422 [7.19, 7.66]  |
| Indiana         | 0.17  | 5.00        | 5.23        | 8.10 [7.88, 8.31]   |
| Iowa            | 0.21  | 4.67        | 4.94        | 7.95 [7.76, 8.15]   |
| Kansas          | 0.17  | 4.41        | 4.59        | 7.76 [7.59, 7.93]   |
| Kentucky        | 0.15  | 5.30        | 5.63        | 7.97 [7.72, 8.21]   |
| Louisiana       | 0.17  | 4.41        | 4.76        | 7.15 [6.88, 7.41]   |
| Maine           | 0.18  | 5.12        | 5.40        | 7.88 [7.65, 8.11]   |
| Maryland        | 0.15  | 4.09        | 4.28        | 7.05 [6.88, 7.22]   |
| Massachusetts   | 0.18  | 3.67        | 3.87        | 6.61 [6.46, 6.76]   |
| Michigan        | 0.19  | 4.56        | 4.77        | 7.49 [7.31, 7.67]   |
| Minnesota       | 0.21  | 3.76        | 3.89        | 7.37 [7.25, 7.49]   |
| Mississippi     | 0.12  | 5.03        | 5.51        | 7.93 [7.57, 8.29]   |
| Missouri        | 0.19  | 4.75        | 5.06        | 7.16 [7.24, 7.68]   |
| Montana         | 0.19  | 4.47        | 4.76        | 7.74 [7.51, 7.97]   |
| Nebraska        | 0.2   | 4.12        | 4.28        | 7.75 [7.62, 7.88]   |
| Nevada          | 0.17  | 4.20        | 4.57        | 7.19 [6.94, 7.45]   |
| New Hampshire   | 0.18  | 4.46        | 4.78        | 7.14 [6.91, 7.37]   |
| New Jersey      | 0.16  | 4.13        | 4.41        | 7.31 [7.08, 7.54]   |
| New Mexico      | 0.15  | 4.37        | 4.71        | 7.32 [7.07, 7.58]   |
| New York        | 0.18  | 4.19        | 4.33        | 7.05 [6.93, 7.17]   |
| North Carolina  | 0.15  | 4.23        | 4.56        | 7.02 [6.74, 7.31]   |
| North Dakota    | 0.24  | 4.46        | 4.71        | 8.23 [8.02, 8.445]  |
| Ohio            | 0.18  | 4.97        | 5.23        | 8.28 [8.07, 8.49]   |
| Oklahoma        | 0.13  | 4.46        | 4.84        | 7.69 [7.37, 8.01]   |
| Oregon          | 0.16  | 4.20        | 4.51        | 6.39 [6.23, 6.56]   |
| Pennsylvania    | 0.19  | 4.41        | 4.67        | 7.48 [7.27, 7.69]   |
| Rhode Island    | 0.17  | 4.45        | 4.79        | 7.12 [6.87, 7.37]   |
| South Carolina  | 0.16  | 4.63        | 4.89        | 7.51 [7.29, 7.72]   |
| South Dakota    | 0.18  | 4.43        | 4.74        | 8.08 [7.83, 8.33]   |
| Tennessee       | 0.13  | 4.86        | 5.25        | 7.31 [7.03, 7.59]   |
| Texas           | 0.18  | 4.73        | 4.98        | 7.28 [7.11, 7.45]   |
| Utah            | 0.12  | 4.57        | 4.86        | 7.94 [7.68, 8.21]   |
| Vermont         | 0.18  | 4.92        | 5.26        | 7.26 [7.04, 7.47]   |
| Virginia        | 0.16  | 4.48        | 4.75        | 7.39 [7.18, 7.59]   |
| Washington      | 0.16  | 4.12        | 4.31        | 6.81 [6.68, 6.94]   |
| West Virginia   | 0.11  | 4.99        | 5.40        | 8.24 [7.89, 8.53]   |
| Wisconsin       | 0.24  | 4.15        | 4.39        | 7.29 [7.10, 7.50]   |
| Wyoming         | 0.18  | 5.14        | 5.65        | 8.25 [7.82, 8.69]   |

Source: Own calculations.

BRFS<sup>a</sup> – Behavioral Risk Factor Surveillance System
Frequency\textsuperscript{1} measures the number of times a respondent binge or heavy drinks in a 30-day period. Intensity\textsuperscript{2} measures the number of alcohol drinks consumed on one occasion in a 30-day period. Means are weighted by population weights and confidence intervals in square brackets.
**eTable 8: Summary of Key Variables NSDUH* 2016-2017**

| Variable                        | Prevaence | Frequency[^1] | Intensity[^2] |
|---------------------------------|-----------|---------------|---------------|
| **Problem Drinker**             | 0.26      | 4.24 [4.18, 4.31] | 3.63 [3.59, 3.68] |
| **Sex**                         |           |               |               |
| Male                            | 0.31      | 4.73 [4.63, 4.83] | 4.12 [4.05, 4.19] |
| Female                          | 0.22      | 3.59 [3.50, 3.67] | 2.98 [2.92, 3.03] |
| **Age**                         |           |               |               |
| 18 to 49 years old              | 0.34      | 4.06 [3.99, 4.12] | 3.83 [3.78, 3.88] |
| 50 to 64 years old              | 0.22      | 4.70 [4.44, 4.96] | 3.31 [3.14, 3.47] |
| 65 or older                     | 0.11      | 4.63 [4.15, 5.11] | 2.84 [2.56, 3.12] |
| **Race**                        |           |               |               |
| White                           | 0.27      | 4.64 [4.55, 4.73] | 3.69 [3.64, 3.75] |
| Black                           | 0.25      | 3.42 [3.26, 3.58] | 3.03 [2.88, 3.18] |
| AIAN                            | 0.24      | 4.59 [4.06, 5.13] | 5.33 [4.89, 5.78] |
| Asian                           | 0.14      | 2.77 [2.51, 3.03] | 2.95 [2.72, 3.19] |
| Other                           | 0.28      | 3.42 [3.29, 3.56] | 3.84 [3.72, 3.97] |
| **Employment**                  |           |               |               |
| Out of the Labor Force          | 0.16      | 4.35 [4.17, 4.53] | 3.59 [3.45, 3.74] |
| Employed                        | 0.33      | 4.16 [4.08, 4.24] | 3.61 [3.56, 3.67] |
| Partime Employment              | 0.26      | 4.27 [4.10, 4.44] | 3.56 [3.46, 3.66] |
| Unemployment                    | 0.32      | 4.73 [4.43, 5.02] | 4.23 [3.99, 4.47] |
| **Education**                   |           |               |               |
| High School                     | 0.23      | 4.24 [4.02, 4.45] | 4.23 [4.03, 4.44] |
| Less than High School           | 0.26      | 4.67 [4.52, 4.83] | 4.06 [3.95, 4.17] |
| Some College or Technical College | 0.28    | 4.34 [4.23, 4.46] | 3.74 [3.67, 3.82] |
| Graduated College Technical College | 0.26  | 3.8 [3.70, 3.91]  | 2.99 [2.93, 3.04] |
| **Income**                      |           |               |               |
| $0 – $50, 000                   | 0.25      | 4.29 [4.14, 4.44] | 3.88 [3.80, 3.95] |
| $50, 000 – $75, 000             | 0.26      | 4.4 [4.27, 4.53]  | 3.64 [3.52, 3.77] |
| > $75, 000                      | 0.29      | 4.21 [4.04, 4.38] | 3.38 [3.31, 3.44] |
| Poor Health                     | 0.20      | 4.51 [3.82, 5.19] | 4.27 [4.05, 4.5]  |
| Life Time Depression Diagnosis  | 0.28      | 4.08 [3.99, 4.18] | 3.34 [3.28, 3.4]  |
| **Health Stressors**            |           |               |               |
| None                            | 0.30      | 4.17 [4.09, 4.25] | 3.64 [3.59, 3.69] |
| One health stressor             | 0.23      | 4.36 [4.22, 4.49] | 3.64 [3.54, 3.75] |
| Two health stressors            | 0.12      | 4.77 [4.10, 5.45] | 3.52 [3.13, 3.92] |
| Three health stressors          | 0.1       | 4.13 [1.78, 6.49] | 2.97 [1.06, 4.89] |
| **Risky Behavior**              |           |               |               |
| Smoker                          | 0.25      | 4.00 [3.92, 4.08] | 3.46 [3.41, 3.52] |
| No Seat Belt                    | 0.35      | 5.62 [5.34, 5.91] | 4.69 [4.49, 4.9]  |
| Risk Taker Test                 | 0.42      | 5.09 [4.95, 5.24] | 4.22 [4.12, 4.32] |
| Driving                         | 0.70      | 5.56 [5.40, 5.71] | 4.02 [3.93, 4.12] |

Source: Own calculations.
**NSDUH**– National Drug Use and Health.

**Frequency** measures the number of times a respondent binge or heavy drinks in a 30-day period.

**Intensity** measures the number of alcohol drinks consumed on one occasion in a 30-day period. Means are weighted by population weights and confidence intervals in square brackets.

### eTable 9: Multicollinearity results for BRFS model without exclusion restriction.

| 2nd Stage Models | Variance Inflation Factor (VIF) | Condition Number |
|------------------|----------------------------------|-----------------|
| Inverse Mills ratio (IMR) regressed on all other covariates | VIF-IMR | 21.04 | 14.42 |
| **Model 1:** BRFS<sup>a</sup> | **Frequency** equation | Mean VIF-X<sub>fi</sub>|<sub>ifj</sub> | 2.82 |
| **Model 2:** BRFS<sup>a</sup> | **Intensity** equation | Mean VIF-X<sub>int</sub>|<sub>ifj</sub> | 2.31 |
| Mean VIF-X<sub>i</sub> | 5.74 | 13.65 |

Source: Own calculations.

<sup>a</sup>BFRS—Behavioral Risk Factor Surveillance System 2016-2017

<sup>1</sup>**Frequency** measures the number of times a respondent binge or heavy drinks in a 30-day period.

<sup>2</sup>**Intensity** measures the number of alcohol drinks consumed on one occasion in a 30-day period.

<sup>3</sup>VIF-IMR (I, F) are the variance inflation factor on the variable IMR when regressed on the rest of the X<sub>i</sub>'s in the frequency and intensity of problem drinking models.

The collinearity diagnostic tables for each covariate VIF<sub>ix</sub> is available upon request.

<sup>4</sup>In practice, VIF on the inverse mills ratio has to be less than 10 and closer to 5 is better. It is a factor responsible for inflating the sampling variance. Values greater than 10 signal a multicollinearity problem and with cause the determinant of X'X degenerate.

<sup>4</sup>The condition number is based on the maximum and minimum Eigen values of the root matrix X'X

In practice, a condition number <100 means there is no significant source of multicollinearity in the model. For values between 100 and 1000 there is danger of multicollinearity and the model is potentially mis-specified, one or more variables are collinear with the rest. A value greater than 1000 means there is systemic multicollinearity and the model is mis-specified.
Appendix Multicollinearity.

1. What is Multicollinearity?

At a very fundamental level multicollinearity is a mathematical property. In matrix algebra we assume that the rank of the matrix with observations on covariates is the same as the number of covariates in the estimated model, and all these covariates are independent of each other. Sometimes the covariates can be expressed as a linear combination of other covariates in the model. For example, including a dummy for male and female, where male is equal to 1 – female. This is an easy spot, other times it may become tricky. In context of selection models, the generated inverse mills ratio maybe a linear combination of all other covariates in the model. When this happens, the matrix becomes ill-conditioned and cannot be inverted. Mathematically,

\[ X = \{X_1, \ldots, X_k\} \]

Let \( X_j \) be the \( j^{th} \) element of this vector. The column vector \( X_1, X_2 \ldots, X_k \) are linearly dependent if there exists a set of constants \( a_1, a_2 \ldots, a_k \), not all zero such that \( \sum_{j=1}^{k} a_j X_j = 0 \) and \( X'X < k \) and \( [X'X]^{-1} \) does not exist.

2. Why does multicollinearity arise?

   a. User-error: linear combinations of the covariates enter into the estimation specification subtly or obviously.
   b. Data collection problems that could arise from sampling over a limited range of covariates in the population.
   c. Constraints on the population from which the sample is drawn.
   d. Having definitional covariates in the estimation, for example income = consumption + savings. A common error would be to include income and savings in estimation.
   e. Adding too many interaction terms, or covariates in estimated model that increases the rank of the matrix, reducing observations to explanatory covariates ratio.

3. What are the consequences if undetected?

Consider a simple model with two covariates

\[ y = \beta_1 X_1 + \beta_2 X_2 + \epsilon, \exists E(\epsilon) = 0 \text{ and } V(\epsilon) = \sigma^2 I \]

\( x_1, x_2 \) and \( y \) are restricted to length 1

Then the simple OLS \( b = [X'X]^{-1} [X'y] \) in this model becomes

\[
\begin{bmatrix}
1 & \rho \\
\rho & 1
\end{bmatrix}
\begin{bmatrix}
b_1 \\
b_2
\end{bmatrix}
=
\begin{bmatrix}
\rho_{1y} \\
\rho_{2y}
\end{bmatrix}
\]

\( \rho \) is the correlation coefficient between \( x_1 \) and \( x_2 \); \( \rho_{jy} \) is the correlation coefficient between \( x_j=1,2 \) and \( y \), \( b = (b_1, b_2)' \) are the estimates of \( \beta \). The variance for this example is simply the same for both \( x_j=1,2 \) that is \( Var(b_1) = Var(b_2) = \frac{\sigma^2}{1-r^2}, Cov(b_1, b_2) = \frac{\rho \sigma^2}{1-r^2}. \)

a) If \( x_1, x_2 \) are uncorrelated then \( r = 0 \) and rank \( [X'X] = 2 \) then, variances are reasonable.

b) If \( x_1, x_2 \) are perfectly correlated then \( r = \pm 1 \) and rank \( [X'X] = 1 \) then, \( Var(b_1) = Var(b_2) = \infty. \) This is inadmissible.

c) We want \( r \to 0 \) because multicollinearity if it arises is considered non-harmful.

d) However, as \( r \to \pm 1 \), existing multicollinearity inflates the variance above acceptable values and is considered harmful because the properties of best linear unbiased predictor are violated. The arising unusually large standard errors may make coefficients insignificant and essential covariates may lose explanatory power. Furthermore, because standard errors are large we will also expect wider confidence intervals around estimated parameters making inference and interpretation unconvincing. Finally, addition and
deletion of covariates will greatly alter the coefficients on the estimated parameters. This is typical of an underlined multicollinearity problem—and signifies a non-robustness in estimation. Ideally, addition or deletion of variables in a model should have little effect on estimated parameters.

4. How do you test for it—rules of thumb?
   a. Take the determinant of $|X'X|$ and correlation matrix, smaller the value more one should suspect multicollinearity. At extreme a zero determinant means perfect multicollinearity. The main limitation of this approach is as a diagnostic it won’t tell you which variable causes the problem, just that a problem exists.
   b. Inspecting the correlation matrix—while inspection of the off-diagonal elements will hint towards a potential multicollinearity if $\rho_{ij}$ are close to 1. This approach will capture all pairwise correlations that signal multicollinearity. It is limited when multiple covariates form a linear combination then pairwise comparison of covariates may not result in large $\rho_{ij}$. For this reason, it is a partial and limited approach to diagnose multicollinearity.
   c. Partial regression-based diagnosis—this is an ad hoc method of figuring out multicollinearity and it gives no information about the underlying relationships between explanatory variables. For example, how many inter-relationships are present in the model and which ones are responsible for multicollinearity. This approach falls under the class of estimations that experienced econometricians call “regression fishing”.
   d. Variance inflation factor (VIF)—this is a clean method of diagnosing multicollinearity problem. In the present context, estimating a Heckman model means we first need to take the inverse mills ratio (IMR) and regress it on the rest of the explanatory covariates. The covariates showing $VIF > 10$ means using the selection model with the specified covariates maybe problematic. Mathematically, let $C = [X'X]^{-1}$ and let $R_j^2$ equal the coefficient of determination of the IMR which is derived by regressing the IMR on the rest of the explanatory variables, then $IMR = X_j$ is regressed on $X_{i\neq j}$ and the jth element of the matrix $C$ is given by $C_{jj} = \frac{1}{1-R_j^2}$. If IMR is orthogonal to the $X_{i\neq j}$’s then $R_j^2$ is small and $C_{jj}$ is close to 1. If otherwise, $C_{jj}$ is large and we have a multicollinearity problem. This $C_{jj}$ is equal to VIF—and the rule of thumb is $1 < VIF < 5$ then do not have to worry about multicollinearity in model. This is an easy test with simple commands in STATA of collin, regression statistics in SPSS has a checkbox for multicollinearity diagnostics, and in R vif is a built-in command for linear estimations. While a high VIF is definitive of a multicollinearity problem it will not shed light on number of dependencies. Higher order tests are needed once a high VIF is detected. VIF should be viewed as the necessary condition for multicollinearity problem—meaning a small VIF bounded between [1, 5] signals proceed with estimation, in current context, estimating the Heckman model is good. To be 100% safe we must do the higher order test and get the condition number.
   e. Condition number—this is the sufficient condition such that a condition number less than 100 means no harmful multicollinearity exists in the specification. In the current example, IMR is not collinear with other explanatory variables in a harmful way and the usage of a Heckman model is context appropriate. This is a second order sufficient condition for passing the multicollinearity test. Any condition number greater than 100 would imply the existing multicollinearity is harmful and the Heckman model should not be used (underlined mathematics upon request). The good thing about condition number
it will tell you which variables generate the problem. In Stata it comes down to a simple commands collin, similarly for other software packages.

5. Oh! No, you have a collinearity problem should you abandon problem covariates? The literature suggests a few mechanisms to fix a multicollinearity problem, if it exists. We briefly discuss refer the interested reader to the standard reference on the topic (Shalabh 2012).
   a. Model re-specification—checking the underlying theory and modeling assumptions will fix most problems. Correct specification, with tight assumptions, is more important than the estimation procedure. Arriving at the correct specification relies on theory, “priors”, data availability, and re-examination of the three. It is an iterative process that often places constraints and the researcher has to either admit defeat or proceed with estimation and explain the data limitations. Either way, the decision to proceed with estimation will depend on the research question and model specification.
   b. Typically, an economist’s mind is more fertile than her data. If possible collecting additional data so the that the researcher is conditioning on the right explanatory variables becomes important. Where collection of additional data is not possible there are corrective methods for dealing with multicollinearity and compromises associated with them.
   c. Eliminate one or two problem covariates if the one of the others in linear combination allows you to infer the other. For example, leaving out male from regression doesn’t harm the estimation process. In other cases, omit default uninformative variables.
   d. Use principal components approach with explanatory variables. Using this approach you can reduce the dimensionality by using a set of linear combinations of explanatory variables so that they retain variability in the system. Typically, you drop the variable with the lowest eigen value. The underlying mathematics of principle components, albeit elaborate, checks out making this a powerful technique to capture the essence of behavior and disease without compromising model specification. With principle component analysis a word of caution goes to the statistician and econometrician who are skeptical; whilst accepting the mathematical legitimacy of the resulting condensed variable they are not as convinced by the interpretability of the resulting regressand. For further details please see (Adam C. 2017 & Hotelling 2013). Used well, principle components will increase the efficiency and correct for multicollinearity. The decision to use principle components approach to deal with multicollinearity in a Heckman model is context dependent that is, the researcher must ask how important is it to correct for the selection bias.
   e. Ridge Estimation—this is an uncommon approach where you accept the minimum variance biased estimator (see Shalabh 2012).