Unemployment and Risky Behaviours: The Effect of Job Loss on Alcohol and Tobacco Consumption

Jérôme Ronchetti* and Anthony Terriau**

Abstract – This article analyses the impact of a transition from employment to unemployment on alcohol and tobacco consumption, and more specifically on risky behaviours. With cross-section data, we observe significant differences between the employed and the unemployed both in terms of frequency and quantity consumed. However, this association between unemployment and risky behaviours disappears when we use longitudinal data and a difference-indifferences propensity score matching approach to reduce the selection bias. Our results suggest that, in the French context, the event of unemployment does not lead to a significant increase in risky behaviours.

JEL Classification: C23, I10, I12, I18
Keywords: unemployment, tobacco, alcohol, addictions

** Magellan, Université Jean Moulin Lyon 3, Iaelyon School of Management (jerome.ronchetti@univ-lyon3.fr); ** GAINS, Le Mans Université (anthony.terriau@univ-lemans.fr)*
The authors would like to thank two anonymous reviewers for the valuable comments.
Received in March 2019, accepted in January 2020. Translated from “Chômage et comportements à risque : quel effet de la perte d'emploi sur la consommation d'alcool et de tabac ?”

Citation: J. Ronchetti & A. Terriau (2021). Unemployment and Risky Behaviours: The Effect of Job Loss on Alcohol and Tobacco Consumption. *Economie et Statistique / Economics and Statistics*, 522-523, 23–41. https://doi.org/10.24187/ecostat.2021.522d.2039

The interaction between health and unemployment has attracted a growing interest for several years, particularly following the rise in unemployment observed after the 2008 financial crisis. Some of the literature, based on simple correlations, shows a strong association between unemployment and health. However, we cannot infer from this that unemployment has a negative causal effect on health. Firstly, there is a selection bias: the youngest individuals, for example, have a higher probability of being unemployed (Gervais *et al*., 2016). Some authors have also shown the existence of a reverse causality: workers in poor health have a greater probability of losing their jobs (Jusot *et al*., 2008). Moreover, unemployed people in weak health have more difficulty finding or staying in employment (Barnay & Defebvre, 2016). These factors may explain why we observe a higher proportion of individuals in poor health within the unemployed population, even in the absence of any causal effect of unemployment on health.

There are several methods for identifying the health effect of unemployment. One initial method consists of using an exogenous event that results in unemployment. Salm (2009) and Schmitz (2011) use business closures in the USA and Germany respectively, and show that the experience of unemployment does not have any significant impact on health. In France, business closures are rarer than in the USA or Germany and several mechanisms allow firms to part with their workers prior to the permanent closure of their business (mutually agreed contract termination, redundancy, etc.). Consequently, this approach cannot be used in the case of France.[1] A second approach consists of using propensity score matching methods. Research conducted by Browning *et al*. (2006), Böckerman & Ilmakunnas (2009), Gebel & Voßemer (2014), and Ronchetti & Terriau (2019; 2020) in Denmark, Finland, Germany and France respectively, conclude in this way that the experience of unemployment has no significant effect on state of health. While unemployment does not appear to have any significant short-term impact on health, it is possible, however, that it may lead to a change in living habits and addictive behaviour that could have a longer term impact on health. The work of Marcus (2014), based on German data, shows that losing their job encourages those who did not used to smoke to start smoking but does not increase cigarette consumption by individuals who were already smokers.

There are multiple ways in which alcohol and tobacco consumption may be influenced during a spell of unemployment. Firstly, if alcohol and tobacco are normal goods, the drop in income due to job loss should lead to reduced consumption of both these goods (Hill, 2003; 2014). However, Peretti-Watel *et al*. (2009) observe a higher prevalence of smoking among the poorest individuals. Jarvis & Wardle (1999) showed that the deterioration in lifestyle sometimes observed in the event of a negative shock can be explained by the individual's need to compensate "psychologically" for their short-term social and economic difficulties. The experience of unemployment has been said to be associated with an increase in stress, a greater preponderance of somatic, depressive and anxiety syndromes and a more general deterioration in mental health (Linn *et al*., 1985; Osipow & Fitzgerald, 1993; Bartley & Owen, 1996; Thomas *et al*., 2005; Burgard *et al*., 2007; Tefft, 2011; Gathergood, 2013; Blasco & Brodaty, 2016). The psychological shock caused by job loss might then lead to an increase in risky behaviour through excessive consumption of alcohol, cigarettes or medicinal substances (Peck & Plant, 1986; Lee *et al*., 1991; Morris *et al*., 1992; Montgomery *et al*., 1998; Falba *et al*., 2005; Kuhn *et al*., 2009; Browning & Heinesen, 2012; Classen & Dunn, 2012; Ahmed & Peeran, 2016).

Some of the literature concerns the relationship between consumption of alcohol and tobacco. Several studies suggest the existence of a kind of complementarity between these two goods (Tauchmann, 2013). Drinkers of alcohol are said to have a greater probability of smoking and smokers a greater propensity to drink alcohol (Shiffman & Balabanis, 1995; Madden & Heath, 2002; Falk *et al*., 2006; De Leon *et al*., 2007). Several studies show that a price rise or the lowering of the legal age for consuming one of these goods translates into a fall in consumption of both goods (Dee, 1999). Laboratory tests tend to show that alcohol stimulates tobacco consumption (Mintz *et al*., 1985; Mello *et al*., 1987) while nicotine encourages people to drink more alcohol (Acheson *et al*., 2006; Barrett *et al*., 2006). Consequently, it is necessary to analyse the effect of unemployment both on alcohol consumption and on tobacco consumption.

Analysis of the effects of unemployment on alcohol and tobacco consumption is of great relevance from a public health perspective. Tobacco

1. The Labour Force Survey allows identifying individuals who have lost their job following the closure of a business and, as from 2013, includes state of health variables. However, the sample obtained is too small for our purposes.

can cause many pathologies, in particular different types of cancer, lung pathologies and cardiovascular disease (Sturm, 2002; Bjartveit & Tverdal, 2005). Alcohol, in turn, can cause neurological diseases and cognitive impairment and can trigger cardiovascular or digestive problems (Anderson *et al*., 1993; Edwards, 1997; Nelson *et al*., 2013; Praud *et al*., 2016; Connor, 2017). According to the French Ministry for Solidarity and Health, these are the two main causes of avoidable mortality in France. Several studies consider tobacco consumption to be the cause of nearly 20% of deaths, whilst consumption of alcohol is said to be responsible for about 3.5% of deaths in developed countries (Peto *et al*., 1992; McGinnis & Foege, 1993; Mokdad *et al*., 2004; Danaei *et al*., 2009; Ma *et al*., 2018). Moreover, a significant proportion of health expenditure is attributable to consumption of these two substances (Xu *et al*., 2015; Miquel *et al*., 2018). It would therefore appear to be essential to analyse whether unemployment may contribute to increased consumption of alcohol and tobacco and to the development of risky behaviour. Such an analysis is all the more important as the pathologies attributable to alcohol and tobacco may arise several years later. Most studies that assess the effect of unemployment on health are based on indicators of perceived health, measurements of mental health or health care consumption in the short term. However, it is possible that some effects of unemployment on health may only be perceived in the long term, beyond the time periods generally observed in surveys conducted in France (Blasco & Brodaty, 2016, using SIP – *Santé et Itinéraire Professionnel*, a survey on health and professional career; Ronchetti & Terriau, 2020, with the ESPS – *Enquête Santé et Protection Sociale*, a survey on health, access to healthcare and insurance; and Ronchetti & Terriau, 2019, using the *Enquête Emploi*, the French Labour Force Survey). In the case of France, one way of analysing the potential impact of unemployment on health beyond the survey periods (a maximum of 4 years for most French longitudinal surveys) consists of observing whether there are any short-term changes in addictive or risky behaviour, liable to have an impact on health in the longer term.

If unemployment causes a rise in risky behaviour in terms of consumption of alcohol and tobacco, the public authorities must take into consideration the negative externalities of unemployment as regards health and further increase their efforts to tackle unemployment. Moreover, if unemployment leads to an increase in addictive behaviour, this is likely to last well beyond the period of unemployment. Indeed, it has been shown that excessive or regular consumption of alcohol or tobacco leads to increased risk of absenteeism and a reduction in work productivity (Batenburg & Reinken, 1990; Halpern *et al*., 2001; Rice *et al*., 1998; Norström, 2006). Alcoholism and smoking are also associated with a lower probability of finding work and an increased risk of unemployment (Johansson *et al*., 2007; Mullahy & Sindelar, 1996; MacDonald & Shields, 2004). Consequently, the economic cost of a rise in risky behaviour and addiction may be highly significant and demands special attention.

Lastly, the economic, social and institutional environment may have a significant influence on the relationship between unemployment and consumption of alcohol and tobacco. On the one hand, alcohol and tobacco are heavily taxed products and vary greatly in price from one country to another. On the other hand, the net replacement ratio, i.e. the income an unemployed person receives as a percentage of their old salary, is dependent on the specific unemployment insurance and welfare systems for each country. As emphasised by Ahn *et al.* (2004), this net replacement ratio may influence the way in which a period of unemployment is experienced. It may affect consumption of alcohol and tobacco through the role it plays in stress and mental health (precursors) but also through the shock to income caused by job loss. Consequently, the impact of unemployment on consumption of alcohol and tobacco may vary greatly by country, especially if there is a significant income effect. Lastly, although some studies have already been conducted to examine the interaction between unemployment and risky behaviour, they generally concerned countries with relatively low rates of unemployment, of relatively short duration (Germany, the USA, Scandinavian countries, etc.). In France, where the unemployment rate is higher and the average duration of unemployment is longer than a year, the experience of unemployment may feel noticeably different. So the effects measured in other countries are not transposable to France.

In this article, we assess the impact of unemployment on consumption of alcohol and tobacco using data from the ESPS survey over the 2010-2014 period. We deploy a difference-in-difference estimation method with propensity score matching and show that the experience of unemployment does not cause a change in risky behaviour. The rest of this article is structured as follows: Section 1 briefly introduces the differences in health and risk behaviour between unemployed and employed individuals, then Section 2 details the econometric strategy. Section 3 gives the main results and a sensitivity analysis is provided in Section 4. Then we conclude and present possible further developments.

1. The Gap between the Unemployed and the Employed in Terms of Health and Alcohol and Tobacco Consumption

In order to motivate our study, we present the main differences between unemployed people and those in work as regards their state of health and consumption of alcohol and tobacco, observed on the basis of data from the ESPS survey. The data, the sample and main variables of interest are presented in Box 1.

Figure I shows individuals who were unemployed in 2014 to be in significantly poorer health than those in work[2] (significance level of 5%). While there may be no statistical difference between the two populations in terms of the percentage of individuals drinking alcohol

2. *Tests not reported here. Tests on variables observed in 2010 for these two groups are shown in Table 2 (See "Unmatched" sample).*

Box 1 – **Data, Sample and Outcome Variables**

Data

The ESPS (*Enquête Santé & Protection Sociale* – a survey on health, access to healthcare and insurance) has been conducted since 1988 by IRDES (Institut de Recherche et Documentation en Économie de la Santé / Institute for Research and Information in Health Economics). The survey collects data on the employment status, state of health and living habits. This is the first longitudinal database providing information simultaneously on work trajectories and consumption of alcohol and tobacco. It is a panel survey that questions the same households every 4 years. The sample was entirely redrawned in 2010 to reduce attrition between the different survey waves. In our study, we use the 2010 and 2014 surveys, which are representative of about 97% of the population living in Metropolitan France.

Sample

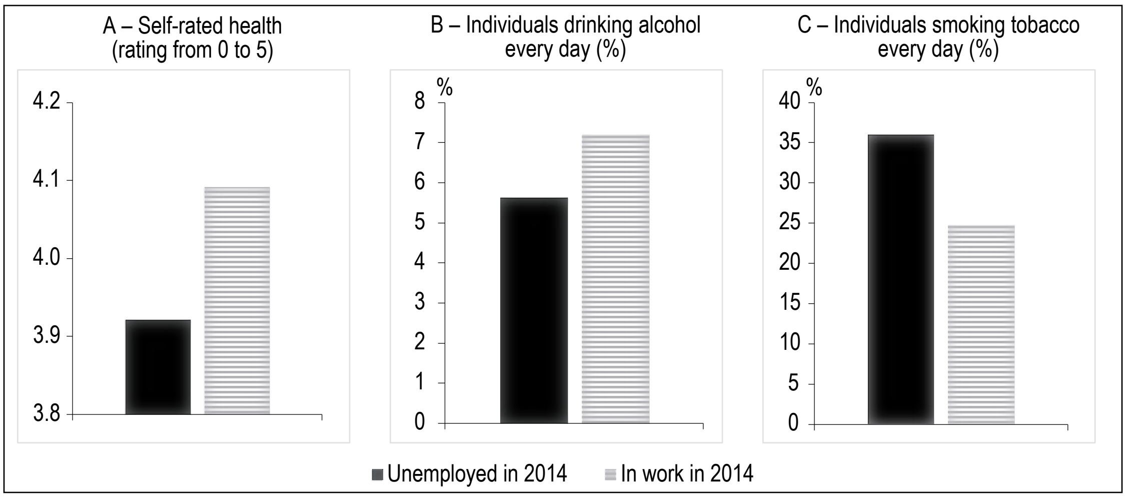
Our sample consists of people in work in 2010, who are either in work or unemployed in 2014. We therefore focus on individuals with a strong attachment to the labour market. Students, pensioners and other inactive individuals are excluded from the analysis, resulting in a sample of 1,540 individuals. We then exclude individuals not in the common support of the distribution of scores (13 individuals). The final sample consists of 1,527 individuals. About 90% of them are in work in 2010 and 2014 (control group) and nearly 10% are in work in 2010 but out of work in 2014 (treated group).

Outcome Variables

Our study examines the impact of the experience of unemployment on short-term health but also on behaviour that is likely to cause a deterioration in health in the longer term. To that end, we make use of three series of outcome variables. The first one relates to health. Firstly, we use the "Self-rated health" variable, based on responses to the following question: "What is your general state of health?" on a scale of 1-5, where 1 = "Very Good", 2 = "Good", 3 = "Quite Good", 4 = "Poor" and 5 = "Very Poor". In the article, we reverse this scale such that 1 is regarded as a "Very Poor" state of health and 5 as a "Very Good" state of health. We also create a dichotomous "Poor Health" variable, equal to 1 if the individual rates their state of health as "Quite good", "Poor" or "Very poor", and equal to 0 if the individual rates their state of health as "Good" or "Very good". Additionally, we use a binary "Depression"[(a)] variable, equal to 1 if the individual stated they had depression and 0 if not. Consequently, we have overall measurements of state of health and a more specific mental health-related measurement. A second series of outcome variables is aimed at analysing alcohol consumption habits. Firstly, we study consumption frequency through the "Drinks every day" ("Drinks occasionally") variable, equal to 1 if the individual consumes alcohol daily (occasionally) and 0 if not. In the second stage, we analyse the amount consumed on a single occasion. The survey allows us to find out if an individual "Has 3 or more drinks per occasion" ("Has 5 or more drinks per occasion"). This variable is equal to 1 if the individual has 3 or more drinks (5 or more drinks) per occasion, and 0 if not. We also add variables on alcohol consumption profiles as defined by IRDES (see Appendix). We differentiate between 3 profile types: "Moderate drinker", with a value of 1 if a man (woman) has 21 (14) or fewer drinks per week and never has 6 or more drinks on any one occasion; "Occasional binge drinker", with a value of 1 if a man (woman) has 21 (14) or fewer drinks per week and has 6 or more drinks on one occasion at least twice a month, and "Chronic binge drinker/alcoholic", with a value of 1 if a man (woman) has more than 21 (14) drinks per week or has 6 or more drinks on one occasion at least once a week. Lastly, a third series of outcome variables relates to tobacco consumption. Firstly, we study consumption frequency through the "Smokes every day" ("Smokes occasionally") variable, equal to 1 if the individual smokes daily (occasionally) and 0 if not. We then observe the amount consumed each day through the "Number of cigarettes smoked" variable. All these outcome variables give an overall view of the impact of the experience of unemployment on health and risky behaviour in terms of alcohol and tobacco consumption.

[(a)] Note that this variable is based on answers to the question: "In the last 12 months, have you had a depression?". It is therefore possible that depression preceded the start of unemployment. The results obtained on the basis of this variable must therefore be interpreted with care.

Figure I – **Self-rated health and daily consumers of alcohol and tobacco in 2014**



Sources: IRDES, 2014 ESPS.

every day, the proportion of daily smokers, on the other hand, is significantly higher (at the 5% level) among the unemployed. But are these differences due to unemployment?

To answer this question, it is necessary to use the survey's longitudinal dimension. Figure II shows, in fact, that individuals who were unemployed in 2014 were already significantly in poorer health in 2010 (significance level of 5%), when they were in work. It is therefore possible that the association between unemployment and poor state of health may be a case of reverse causality. Firstly, because individuals in poor health may have a greater probability of becoming unemployed. Secondly, it is possible that, once they become unemployed, they are characterised by relatively long periods of unemployment. These two arguments increase the probability of observing unemployed individuals in poor health. Similar reasoning applies to the link between, on the one hand, unemployment and alcohol[3] and, on the other, between unemployment and tobacco.[4] The following section presents the econometric strategy used to minimise selection bias and identify the effect of unemployment on health and on risky behaviour.

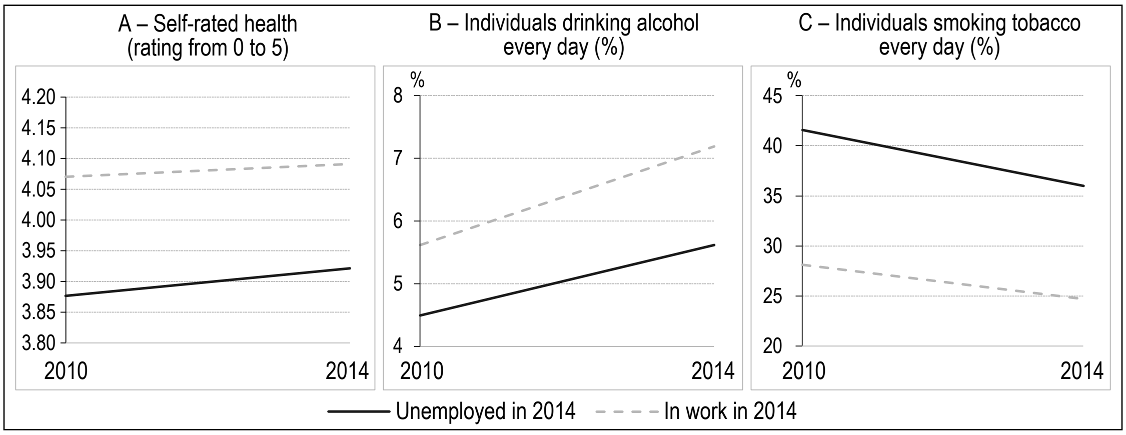
2. Empirical Strategy

We use a difference-in-difference estimation method with propensity score matching (Box 2) to identify the impact of the experience of unemployment on health and on risky behaviour. This method, which is appropriate to samples of a modest size (Pirracchio *et al.*, 2012), consists of matching individuals from the test group and control group on their propensity to be treated, then comparing the average change in the outcome variable for the treated group and the untreated group. Several stages need to be

3. There is no statistical difference (significance level of 5%) in the rates for daily drinkers of alcohol, as measured in 2010, whether in work or unemployed in 2014.

4. There is no statistical difference (significance level of 5%) in the rates for daily cigarette smokers, as measured in 2010, whether in work or unemployed in 2014.

Figure II – **Self-rated health in 2010 and daily consumers of alcohol and tobacco in 2014**



Sources: IRDES, 2010-2014 ESPS.

Box 2 – **Estimation Strategy**

Our sample is made up exclusively of people in work in 2010. Let D be the treatment, with $D=0$ if the individual is in work in 2014 and $D=1$ if the individual is unemployed. Let Y be the outcome variable (state of health, consumption of alcohol or tobacco) with Y^1 the outcome variable for a member of the treatment group and Y^0 the outcome variable for a person in the control group. If we consider $t=2010$ and $t+1=2014$, according to the Difference-in-Difference (DiD) approach, the Average Treatment effect on the Treated (ATT) is determined by comparing the change in outcome variable between t and $t+1$ for the treatment group $E\left(Y_{t+1}^1 - Y_t^1 \mid D=1\right)$ with that for the control group $E\left(Y_{t+1}^0 - Y_t^0 \mid D=1\right)$, that is to say:

$$ATT = E\left(Y_{t+1}^1 - Y_t^1 \mid D=1\right) - E\left(Y_{t+1}^0 - Y_t^0 \mid D=0\right)$$

Under the two-group common trend assumption, which assumes that, in the absence of treatment, the individuals in the treatment group and those in the control group would have a similar change in their outcome variables, then:

$$E\left(Y_{t+1}^0 - Y_t^0 \mid D=1\right) = E\left(Y_{t+1}^0 - Y_t^0 \mid D=0\right)$$

There are several advantages to the difference-in-difference approach. The first difference, consisting on one side of the equation of $E\left(Y_{t+1}^1 - Y_t^1 \mid D=1\right)$ and on the other of $E\left(Y_{t+1}^0 - Y_t^0 \mid D=0\right)$ allows individual fixed effects to be eliminated, while the second difference $E\left(Y_{t+1}^1 - Y_t^1 \mid D=1\right) - E\left(Y_{t+1}^0 - Y_t^0 \mid D=0\right)$ allows common temporal effects to be eliminated. However, in our case it is not possible to apply the difference-in-difference approach directly as treatment allocation is not random. Indeed, Table 1 shows, for example, that the youngest individuals, those on fixed-term contracts and people in poor health in 2010 have a higher probability of being unemployed in 2014. One possible identification strategy consists of assuming that, given a set of observable characteristics X, the outcome variables are independent of treatment allocation. This conditional independence assumption is written as follows:

$$Y_t^0, Y^1 \perp D \mid X$$

Consequently, it is possible to estimate the ATT by comparing the change in outcome variables between t and $t+1$ of treated and untreated individuals with the same observable characteristics X (Heckman *et al.*, 1998). In order to reduce selection bias, it is preferable to carry out matching on many characteristics that may affect treatment participation. However, as the number of characteristics determining access to treatment rises, it becomes increasingly difficult to find two individuals with exactly the same characteristics. To solve this problem, Rosenbaum & Rubin (1983) propose matching treated and untreated individuals according to a one-dimensional summary called the "propensity score", representing the probability of treatment participation, given a set of observable characteristics X. In this way, they show that, if outcome variable Y is independent of participation in treatment D conditional on the observable characteristics X, it is also independent of D conditional on the propensity score $P(X)$, so:

$$Y_t^0, Y^1 \perp D \mid P(X)$$

under the common support assumption:

$$0 < P(X) < 1$$

This condition makes it possible to ensure that, for each treated individual, there is at least one untreated individual with the same propensity score (Heckman *et al.*, 1998). So, we can minimise selection bias through Propensity Score Matching (PSM). Under the common trend, conditional independence and common support assumptions, we can thus estimate the ATT for individuals in the common support of the distribution of scores, by combining DiD and PSM, that is to say:

$$ATT^{DiD-PSM} \frac{1}{N_{D_1}} \sum_{i \in D_1 \cap S} \left[\left(Y_{i,t+1}^1 - Y_{i,t}^1\right) - \sum_{j \in D_0 \cap S} w_{ij} \left(Y_{j,t+1}^0 - Y_{j,t}^0\right) \right]$$

Where D_1 (D_0) is the treatment group (control group), N the number of treated individuals and S the area of common support. The term w_{ij} represents the weight assigned to the member of the control group with a propensity score close to that of the treated individual, known as "Near Neighbor".

followed to make the estimation credible. Firstly, the propensity score has to be determined, based on a Logit or Probit model, using treatment participation as the dependent variable and all the observable characteristics that may affect treatment participation as independent variables. You then have to ensure that the area of common support for the distribution of the propensity score of both groups is sufficiently broad. Next, a matching algorithm must be selected to match each participant in the programme with the non-participant who appears to have the most similarities. It is then necessary to check that the treatment group and control group display similar average observable characteristics. If matching allows the two groups to be compared, the average treatment effect on the treated (ATT) can then be estimated.

2.1. Propensity Score

The propensity score, i.e. the probability of participating in treatment given a set of observable variables X, is determined with a Probit model, using treatment participation as the dependent variable (Imbens & Wooldridge, 2009). In order for the conditional independence assumption to be credible, the estimation of the propensity score must include all the variables that may have a significant influence on treatment participation (Table 1). The explanatory variables we use are measured in 2010, prior to treatment allocation, so as to avoid endogeneity problems. Here we select: age, age squared, gender, level of education, marital status, household income, socio-professional category (CSP), business sector and company size, contract type, and variables related to the state of health and the consumption of alcohol and tobacco. Estimating the propensity score enables us to minimise selection bias, whilst including a lagged dependent variable allows us to deal with the problem of reverse causality.

2.2. Quality of the Propensity Score

Use of the propensity score must allow balancing of the distribution of all observable characteristics included when estimating the propensity score $P(X)$. Following estimation, we ensure this balance is verified: we divide the distribution of the propensity score into 10 strata and check, for each of the strata, that there is no statistical difference between the two groups in terms of the average values of the explanatory variables.

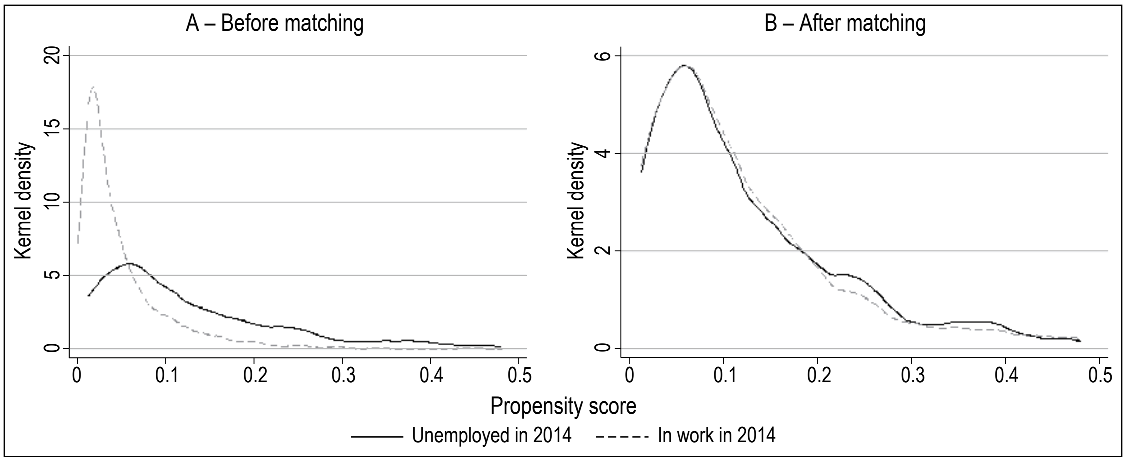
Moreover, use of the propensity score is only appropriate for individuals in the common support of the distribution of scores. Figure III (left side) shows that, prior to matching, the area of common support is relatively broad (Lechner, 2002). We adopt the Min-Max method suggested by Dehejia & Wahba (2002), which consists of retaining only those individuals for whom there

Table 1 – **Probit model**

	Coefficient	Standard Error
Age	-0.1838***	0.0622
Age²	0.0023***	0.0009
Male *(ref. Female)*	-0.2104	0.1287
Education level *(ref. Tertiary)*		
Primary	0.0205	0.4404
Lower secondary	-0.0175	0.1687
Upper secondary	-0.1936	0.1740
Married *(ref. Unmarried)*	-0.1679	0.1278
Household Income *(ref. > €4,600)*		
< €1,300	0.0823	0.2485
€1,300 - €4,600	-0.1109	0.1846
Socio-Professional Category *(ref. Other)*		
Clerical, sales & services/blue-collar	0.0872	0.2151
Middle-level occupation	-0.2020	0.2223
Sector *(ref. Other)*		
Agriculture, forestry, fishing	-0.1276	0.4198
Industry	0.2653	0.1793
Construction	0.3123	0.2375
Trade and services	0.2063	0.1472
Company size *(ref. 20 or more employees)*		
Less than 10 employees	0.5291***	0.1623
Between 10 and 19 employees	0.5847***	0.2020
Permanent contract *(ref. Fixed-term)*	-0.3458**	0.1419
State of Health		
Self-rated health	-0.2073***	0.0794
Alcohol consumption *(ref. None)*		
Drinks every day	-0.1877	0.2768
Drinks occasionally	-0.3059**	0.1372
Tobacco consumption *(ref. None)*		
Smokes every day	0.2045	0.1256
Smokes occasionally	0.2225	0.2432
Number of observations	1,540	

Notes: All variables are measured in 2010, prior to treatment allocation. Significance levels: 10% (*), 5% (**), 1% (***).
Sources: IRDES, ESPS 2010.

Figure III – **Distribution of the propensity score, before and after matching**



Sources: IRDES, 2010-2014 ESPS.

is a counterfactual. Consequently, individuals whose score is lower than the minimum value or higher than the maximum value of the score in the other group are excluded from the analysis.[5]

2.3. Matching

Each member of the treatment group is then matched with one or more members of the control group with a similar propensity score, referred to as "near neighbors". This matching process may involve several methods. Matching algorithms differ not only in the way in which near neighbors are defined but also in the weight assigned to each near neighbor. First, we match using the Nearest Neighbor method. So each treated individual is matched with 5 members of the control group with the closest propensity score. However, this method, which is frequently used in the literature, may result in bad matches, notably when the nearest neighbors are relatively distant in terms of propensity score. This problem can be solved by setting a maximum propensity score distance, known as "Caliper". Baser (2006) and Caliendo & Kopeinig (2008) show that Caliper matching can significantly reduce selection bias. However, as Smith & Todd (2005) emphasise, the choice of Caliper represents a notable limitation in this approach. Here we rely on the work by Austin (2011) to determine the optimal Caliper size. Lastly, we test the robustness of our matching using a Kernel estimator (Heckman *et al.*, 1998). So each individual in the control group participates in the construction of the counterfactual of a treated individual, with a weighting that is dependent on the distance between their propensity score and the score of the individual under consideration. Consequently, individuals in the control group with a closer propensity score, relatively speaking, are given a higher weighting. This method helps to reduce variance as more information is used. The ATT (average treatment effect on the treated, see Box 2) is then estimated for each of these matching algorithms (Nearest Neighbor, Caliper and Kernel).

2.4. Quality of Matching

The final stage consists in examining the extent to which use of the propensity score helps reduce selection bias. Figure III shows the distribution of the propensity score, before and after matching, for individuals who have become unemployed (treatment group) and for those still in work in 2014 (control group). While the chart on the left reveals a marked difference in the distribution of the score for the two groups before matching, the chart on the right shows that the distribution of the propensity score becomes similar in both groups after matching. In other words, matching seems to have made individuals in the treatment group comparable with those in the control group. The quality of matching may be assessed firstly by comparing the average characteristics within both groups before and after matching (Rosenbaum & Rubin, 1985a; 1985b). Table 2 shows that the differences initially observed between treated and untreated individuals are no longer significant once the matching is done. Additionally, it is possible to determine the reduction in bias initially observed (Caliendo & Kopeinig, 2008). The bias corresponds to the difference in averages between treated and untreated individuals, divided by the common standard deviation of the sample. The reduction in bias is determined by a comparison between

5. As the area of common support is particularly broad, the Min-Max method leads us to exclude only 13 individuals from the analysis. Our final sample therefore consists of 1,527 individuals.

the bias calculated for the matched sample and then the unmatched sample. Table 2 shows that matching led to a considerable reduction in bias for all the characteristics for which significant differences in average were initially observed between the two groups.

3. Results

We now compare the change in the outcome variables between t and $t+1$ for individuals in the treatment group and members of the control group. First, we analyse the effect of unemployment on health and then the impact of unemployment on consumption of alcohol and tobacco. In this way, we explore the effects of unemployment on short-term health but also on behaviour that is likely to cause a deterioration in health in the longer term. To measure the state of health, we use the three outcome variables described in Box 1: firstly, individuals' self-rated health, on a scale of 1 to 5 ("1" being the poorest state of health and "5" the best).

Table 2 – **Average characteristics in 2010 of unemployed individuals and people in work in 2014, before and after matching**

	Sample	Unemployed in 2014	In work in 2014	Difference	Bias (%)	Reduction in bias (%)
Age	Unmatched	35.24	38.57	-3.33***	-38.8	
	Matched	35.28	35.38	-0.10	-1.2	96.9
Age²	Unmatched	1331	1545	-214***	-34.6	
	Matched	1334	1329	5	0.9	97.5
Male *(ref. Female)*	Unmatched	0.4494	0.5017	-0.0523	-10.5	
	Matched	0.4419	0.4767	-0.0348	-7.0	33.3
Education level *(ref. Tertiary)*						
Primary	Unmatched	0.0225	0.1370	-0.1145	6.6	
	Matched	0.0233	0.0233	0.0000	0.0	100
Lower Secondary	Unmatched	0.4607	0.3587	0.1020*	20.8	
	Matched	0.4535	0.5465	-0.0930	-19.0	8.8
Upper Secondary	Unmatched	0.2360	0.2409	-0.0049	-1.2	
	Matched	0.2326	0.1977	0.0349	8.2	-601.1
Married *(ref. Unmarried)*	Unmatched	0.4607	0.6660	-0.2053***	-42.2	
	Matched	0.4767	0.5581	-0.0814	-16.7	60.4
Household Income *(ref. > €4,600)*						
< €1,300	Unmatched	0.1512	0.0680	0.0832***	26.8	
	Matched	0.1512	0.1279	0.0233	7.5	72
€1,300 - €4,600	Unmatched	0.7326	0.7890	-0.0564	-13.2	
	Matched	0.7326	0.7093	0.0233	5.4	58.8
Socio-Professional Category *(ref. Executives)*						
Clerical, sales & services/blue-collar	Unmatched	0.7640	0.5750	0.1890***	40.9	
	Matched	0.7558	0.7558	0.0000	0.0	100
Middle-level occupation	Unmatched	0.1461	0.2663	-0.1202**	-30.0	
	Matched	0.1512	0.1628	-0.0116	-2.9	90.3
Sector *(ref. Other)*						
Agriculture, forestry, fishing	Unmatched	0.0225	0.0200	0.0025	1.8	
	Matched	0.0233	0.0116	0.0117	8.1	-343.4
Industry	Unmatched	0.1573	0.1789	-0.0216	-5.7	
	Matched	0.1628	0.2093	-0.0465	-12.4	-117.9
Construction	Unmatched	0.1011	0.0623	0.0388	14.2	
	Matched	0.1047	0.0814	0.0233	8.5	40.1
Trade and services	Unmatched	0.4270	0.3381	0.0889	18.3	
	Matched	0.4186	0.4186		0.0	100
Company size *(ref. 20 or more employees)*						
Less than 10 employees	Unmatched	0.2360	0.1027	0.1333***	36.0	
	Matched	0.2326	0.2093	0.0233	6.3	82.6
Between 10 and 19 employees	Unmatched	0.1236	0.0479	0.0757***	27.2	
	Matched	0.1279	0.1512	-0.0233	-8.3	69.3
Permanent contract *(ref. Fixed-term)*	Unmatched	0.6629	0.8200	-0.1571***	-36.3	
	Matched	0.6628	0.6861	-0.0233	-5.4	85.2

➔

Table 2 – *(contd.)*

	Sample	Unemployed in 2014	In work in 2014	Difference	Bias (%)	Reduction in bias (%)
State of Health						
Self-rated health	Unmatched	3.8764	4.0705	-0.1941**	-24.9	
	Matched	3.8837	3.8256	0.0581	7.5	70
Alcohol consumption *(ref. None)*						
Drinks every day	Unmatched	0.0449	0.0561	-0.0112	-5.1	
	Matched	0.0465	0.0233	0.0232	10.6	-108
Drinks occasionally	Unmatched	0.6742	0.7680	-0.0938*	-21.0	
	Matched	0.6861	0.6163	0.0698	15.6	25.6
Tobacco consumption *(ref. None)*						
Smokes every day	Unmatched	0.4157	0.2813	0.1344**	28.4	
	Matched	0.3954	0.4070	-0.0117	-2.5	91.3
Smokes occasionally	Unmatched	0.0674	0.0540	0.0134	5.6	
	Matched	0.0698	0.1163	-0.0465	-19.4	-248.6
Number of observations	1,527					

Notes: See Table 1.
Sources: IRDES, ESPS 2010-2014.

Following Böckerman & Ilmakunnas (2009) and Gebel & Voßemer (2014), we regard self-rated health as a cardinal measure and we estimate the ATT. Although this is a subjective measure of the state of health, several studies have demonstrated the ability of this scale to reflect individuals' objective state of health and its predictive value in terms of morbidity and mortality (Burström & Fredlund, 2001; Connelly *et al.*, 1989; Franks *et al.*, 2003; Grant *et al.*, 1995; Idler & Angel, 1990; Idler & Benyamini, 1997; Idler & Kasl, 1995; Lundberg & Manderbacka, 1996; McCallum *et al.*, 1994; Okun *et al.*, 1984). Additionally, we use a "Poor health" variable, equal to 1 if the individual rates their state of health as "Quite good", "Poor" or "Very poor", and equal to 0 if the individual rates their state of health as "Good" or "Very good". In this way, we measure the effect of unemployment on self-rated health and on the probability of being in poor health. We also use a third outcome variable, "Depression", equal to 1 if the individual states they have had depression and 0 if not. This last variable enables us to assess the effect of unemployment on mental health. Regardless of the health variable used, our estimates show that, in the case of France, the experience of unemployment has no significant impact on health, at least in the short term. (Table 3-A).

We then examine the impact of unemployment on behaviour in terms of consumption of alcohol and tobacco. Alcohol consumption can be assessed from different perspectives. Firstly, we estimate the effect of unemployment on the probability of drinking alcohol, whether on a daily basis or occasionally (Table 3-B). In the former case, the ATT are close to 0 and non-significant, which implies that the experience of unemployment has no effect on the probability of consuming alcohol on a daily basis. In the case of occasional consumption, the ATT are significant only at a significance level of 10% with the nearest neighbor or Kernel matching, and at a significance level of 5% with Caliper matching.

Although the experience of unemployment may have moderate effects on frequency of consumption, it may possibly lead, however, to a substantial change in the volume consumed on each occasion. We examine whether becoming unemployed had an impact on the probability of having three or more drinks and then on the probability of having five or more drinks on a single occasion. We do not identify any significant effect. Lastly, we analyse the impact of unemployment on alcohol consumption profiles as defined by IRDES (see Appendix). We thus differentiate between non-drinkers of alcohol, moderate drinkers, occasional binge drinkers and chronic binge drinkers/alcoholics. Our estimation show that unemployment causes a slight reduction in moderate consumption, only significant at a significance level of 10% with the nearest neighbor matching (Table 3-C). While unemployment may lead to a change in alcohol consumption practices, it only seems to influence behaviour that poses a low risk to health.

We now turn to the impact of unemployment on smoking. This issue is central to our analysis, on the one hand because tobacco is the primary cause of premature mortality in France and, on the other, because our unmatched data indicated that daily smokers represent a significantly

Table 3 – **Average treatment effect on the treated (ATT)**

A – Outcome variable: Health

Treatment	Matching algorithm	Dependent Variable: Self-rated health	Poor health	Depression
Unemployment in 2014	Nearest Neighbor	-0.0349	0.1047	0.0233
		(0.1288)	(0.0757)	(0.0506)
	Caliper	-0.0238	0.1071	0.0357
		(0.1283)	(0.0758)	(0.0501)
	Kernel	-0.0358	0.0813	-0.0026
		(0.1007)	(0.0557)	(0.0362)

B – Outcome variable: Alcohol consumption, quantity

Treatment	Matching algorithm	Dependent Variable: Drinks every day	Drinks occasionally	Has 3 or more drinks per occasion	Has 5 or more drinks per occasion
Unemployment in 2014	Nearest Neighbor	-0.0350	-0.1163*	-0.0814	0.0698
		(0.0832)	(0.0599)	(0.0643)	(0.0436)
	Caliper	-0.0238	-0.1190**	-0.0833	0.0714
		(0.0841)	(0.0609)	(0.0652)	(0.0442)
	Kernel	-0.0240	-0.0741*	-0.0389	0.0376
		(0.0634)	(0.0432)	(0.0436)	(0.0247)

C – Outcome variable: Alcohol consumption, type of drinker

Treatment	Matching algorithm	Dependent Variable: Moderate drinker	Occasional binge drinker	Chronic binge drinker / alcoholic
Unemployment in 2014	Nearest Neighbor	-0.0814**	-0.0233	-0.0116
		(0.0775)	(0.0764)	(0.0440)
	Caliper	-0.0833	-0.0357	0.0001
		(0.0788)	(0.0766)	(0.0428)
	Kernel	-0.0744	-0.0640	0.0471
		(0.0596)	(0.0561)	(0.0300)

D – Outcome variable: Tobacco consumption

Treatment	Matching algorithm	Dependent Variable: Smokes every day	Smokes occasionally	Number of cigarettes smoked
Unemployment in 2014	Nearest Neighbor	-0.0465	0.0465	-1.7209*
		(0.0544)	(0.0456)	(0.9412)
	Caliper	-0.0476	0.0476	-1.9762**
		(0.0554)	(0.0464)	(0.9519)
	Kernel	0.0098	-0.0235	-0.2067
		(0.0440)	(0.0347)	(0.7825)

Notes: Number of observations = 1,527. Standard errors, shown in brackets, obtained by bootstrap (100 replications). Significance levels: 10% (*), 5% (**), 1% (***).
Sources: IRDES, ESPS 2010-2014.

higher proportion of the unemployed population than of people in work. As before, we examine the impact on the proportion of consumers and then on the amount consumed. Our results suggest that the experience of unemployment has no significant impact on the probability of smoking daily or occasionally (Table 3-D). Moreover, unemployment has a negative effect on the number of cigarettes smoked. This reduction in amount of tobacco smoked might be partly explained by the drop in income caused by job loss. However, the effects do not withstand a change in matching algorithm and are not significant with a kernel estimator.

4. Sensitivity Analysis

Special attention must be paid to the assumption of conditional independence, as emphasised by Bléhaut & Rathelot (2014). Indeed, matching methods are based on the assumption that the underlying results and treatment allocation are independent conditional on a set of observable variables X, i.e.:

$$Y^0, Y^1 \perp D|X$$

In this section, we propose assessing the sensitivity of our estimates to a deviation from the conditional independence assumption. For that, we follow the method suggested by Ichino *et al.*, (2008). Let us suppose that the conditional independence assumption is no longer met but that it would be, given a set of observable variables X and an unobserved binary variable U.

$Y^0, Y^1 \perp D \mid (X,U)$

In this case, if we know U, it is possible to estimate the ATT. The distribution of the unobserved binary variable U is characterised by specifying the following four parameters:

$$p_{mn} = \Pr(U=1 \mid D=m,\ Y=n) = \Pr(U=1 \mid D=m,\ Y=n, X)$$

with $m,n \in \{0,1\}$, which gives the probability that $U = 1$ in each of the 4 groups defined by treatment variable D and outcome variable Y. Given the parameters p_{mn}, a value of U is attributed to each individual, depending on the group to which they belong. U is then included in the set of variables for determining the propensity score and the ATT is then estimated using the nearest neighbor method. This process is repeated 1,000 times to determine an average ATT out of the whole distribution of U.

The effect of U on the outcome variable for untreated individuals (Y^0) is defined as follows:

$$\Gamma = \frac{\dfrac{\Pr(Y=1 \mid D=0,\ U=1, X)}{\Pr(Y=0 \mid D=0,\ U=1, X)}}{\dfrac{\Pr(Y=1 \mid D=0,\ U=0, X)}{\Pr(Y=0 \mid D=0,\ U=0, X)}}$$

and the effect of U on selection in treatment (D) is determined as follows:

$$\Lambda = \frac{\dfrac{\Pr(D=1 \mid U=1, X)}{\Pr(D=0 \mid U=1, X)}}{\dfrac{\Pr(D=1 \mid U=0, X)}{\Pr(D=0 \mid U=0, X)}}$$

Our study includes 13 outcome variables and 3 distinct matching methods. For the sake of clarity, we present here the sensitivity analysis conducted for 2 outcome variables (“Smokes every day” and “Drinks every day”) with a single matching method (Nearest Neighbor). Note that similar results are obtained on other outcome variables used in this study, including when alternative matching methods are used (Caliper and Kernel).

The results are shown in Tables 4 and 5. In each table, the first line indicates the estimated ATT and standard error in the baseline case, i.e. without simulated confounding factor.

Table 4 – **Sensitivity analysis of the average treatment effect on the treated (ATT)**
Outcome variable: “Smokes every day”, matching algorithm: Nearest Neighbor

	p_{ij}				*ATT*	*SE*	*Γ*	*Λ*
	p_{11}	p_{10}	p_{01}	p_{00}				
Without simulated confounding factor (Ref)	0	0	0	0	-0.047	0.054	-	-
Male *(ref. Female)*	0.46	0.40	0.50	0.50	-0.047	0.054	1.035	0.816
Education level *(ref. Tertiary)*								
Primary	0.03	0.00	0.01	0.02	-0.047	0.054	0.661	1.924
Lower secondary	0.44	0.60	0.36	0.33	-0.047	0.054	1.134	1.567
Upper secondary	0.24	0.20	0.23	0.33	-0.047	0.054	0.591	0.999
Married *(ref. Unmarried)*	0.46	0.50	0.67	0.58	-0.047	0.054	1.487	0.448
Household Income *(ref. > €4,600)*								
< €1,300	0.14	0.25	0.07	0.07	-0.047	0.054	1.129	2.564
€1,300 - €4,600	0.74	0.63	0.78	0.86	-0.047	0.054	0.607	0.782
Socio-Professional Category *(ref. Other)*								
Clerical, sales & services/blue-collar	0.77	0.70	0.57	0.68	-0.047	0.054	0.613	2.565
Middle-level occupation	0.14	0.20	0.27	0.22	-0.047	0.054	1.357	0.447
Sector *(ref. Other)*								
Agriculture, forestry, fishing	0.03	0.00	0.02	0.01	-0.047	0.054	1.790	1.451
Industry	0.15	0.20	0.18	0.19	-0.047	0.054	0.917	0.863
Construction	0.11	0.00	0.06	0.05	-0.047	0.054	1.853	1.782
Trade and services	0.41	0.60	0.34	0.30	-0.047	0.054	1.255	1.496
Company size *(ref. 20 or more employees)*								
Less than 10 employees	0.22	0.40	0.10	0.11	-0.047	0.054	0.980	2.823
Between 10 and 19 employees	0.13	0.10	0.05	0.04	-0.047	0.054	1.922	2.895
Permanent contract *(ref. Fixed-term)*	0.66	0.70	0.82	0.80	-0.047	0.054	1.183	0.453

➔

Table 4 – *(contd.)*

	p_{ij}				ATT	SE	Γ	Λ
	p_{11}	p_{10}	p_{01}	p_{00}				
Alcohol consumption *(ref. None)*								
Drinks every day	0.05	0.00	0.05	0.09	-0.047	0.054	0.659	0.793
Drinks occasionally	0.68	0.60	0.77	0.77	-0.047	0.054	0.986	0.660
Tobacco consumption *(ref. None)*								
Smokes every day	0.34	1.00	0.23	1.00	-0.047	0.054		1.829
Smokes occasionally	0.08	0.00	0.06	0.00	-0.047	0.054		1.174
Number of observations	1,527							

Notes: See Table 1.
Sources: IRDES, ESPS 2010-2014.

Table 5 – **Sensitivity analysis of the average treatment effect on the treated (ATT)**
Outcome variable: "Drinks every day", matching algorithm: Nearest Neighbor

	p_{ij}				ATT	SE	Γ	Λ
	p_{11}	p_{10}	p_{01}	p_{00}				
Without simulated confounding factor (Ref)	0	0	0	0	-0.035	0.083	-	-
Male *(ref. Female)*	0.45	0.45	0.48	0.51	-0.035	0.083	0.890	0.867
Education level *(ref. Tertiary)*								
Primary	0.00	0.03	0.03	0.01	-0.035	0.083	5.129	1.944
Lower secondary	0.68	0.34	0.42	0.34	-0.035	0.083	1.451	1.561
Upper secondary	0.23	0.24	0.26	0.23	-0.035	0.083	1.154	0.980
Married *(ref. Unmarried)*	0.55	0.41	0.63	0.68	-0.035	0.083	0.798	0.439
Household Income *(ref. > €4,600)*								
< €1,300	0.10	0.18	0.10	0.06	-0.035	0.083	1.957	2.480
€1,300 - €4,600	0.79	0.70	0.77	0.80	-0.035	0.083	0.882	0.773
Socio-Professional Category *(ref. Other)*								
Clerical, sales & services/blue-collar	0.81	0.74	0.65	0.55	-0.035	0.083	1.553	2.476
Middle-level occupation	0.16	0.14	0.23	0.28	-0.035	0.083	0.737	0.466
Sector *(ref. Other)*								
Agriculture, forestry, fishing	0.00	0.03	0.02	0.02	-0.035	0.083	0.924	1.364
Industry	0.16	0.16	0.16	0.18	-0.035	0.083	0.833	0.831
Construction	0.10	0.10	0.08	0.06	-0.035	0.083	1.362	1.682
Trade and services	0.35	0.47	0.32	0.34	-0.035	0.083	0.908	1.477
Company size *(ref. 20 or more employees)*								
Less than 10 employees	0.16	0.28	0.10	0.10	-0.035	0.083	0.946	2.870
Between 10 and 19 employees	0.06	0.16	0.05	0.05	-0.035	0.083	0.937	2.712
Permanent contract *(ref. Fixed-term)*	0.71	0.64	0.82	0.82	-0.035	0.083	1.030	0.443
Alcohol consumption *(ref. None)*								
Drinks every day	0.13	0.00	0.21	0.00	-0.035	0.083	.	0.841
Drinks occasionally	0.06	1.00	0.14	1.00	-0.035	0.083	.	0.626
Tobacco consumption *(ref. None)*								
Smokes every day	0.42	0.41	0.32	0.27	-0.035	0.083	1.281	1.844
Smokes occasionally	0.03	0.09	0.03	0.06	-0.035	0.083	0.457	1.181
Number of Observations	1,527							

Notes: See Table 1.
Sources: IRDES, ESPS 2010-2014.

In the other lines of the table, the distribution of U is assumed to be comparable to that of other observable variables, such as gender, education, marital status, household income, socio-professional category, business sector and workforce size, contract type, and alcohol and tobacco consumption habits as observed in 2010, i.e. prior to treatment. In all the envisaged configurations, the average treatment effect on the treated (ATT) and standard errors (SE) do not differ from the baseline estimation. All these elements suggest that the results presented in this study withstand a deviation from the conditional independence assumption.

* *
*

The objective of this article is to estimate the impact of the experience of unemployment on individuals' consumption of alcohol and tobacco and, more especially, on risky behaviour. To this end, we use the ESPS survey, which simultaneously gathers panel data on work situation, state of health and consumption of alcohol and tobacco, for the 2010-2014 period. Although a strong association may be observed between unemployment and consumption of alcohol and tobacco with cross-section data, this relationship disappears when using longitudinal data and a difference-in-difference estimation method with propensity score matching to reduce selection bias. Our results suggest that there is little probability of unemployment causing any significant increase in risky behaviour.

This article makes several contributions to the analysis of interaction between work and health. Firstly, it demonstrates the need, in this field of research, to use the data's longitudinal dimension to assess causal effects. It also sheds new light on the causal effect of unemployment on state of health and risky behaviour. While our results appear to be robust, certain limitations must nevertheless be mentioned. Indeed, our study is based on two survey waves, over a 4-year interval. Therefore, we cannot capture all the changes in work status between the two waves of questioning and can only assess the experience of unemployment from a limited perspective. It would be interesting, for example, to analyse the role of the duration of unemployment on consumption of alcohol and tobacco.

This work opens the way to questions that have not yet been explored much in France. Indeed, variables such as physical exercise or dietary habits, not studied in this article, may be influenced by the experience of unemployment and may affect health in the longer term. The development of new, richer longitudinal databases, over a longer timescale, may provide a better understanding of the effect of unemployment on health and expand on the results found. ☐

BIBLIOGRAPHY

Acheson, A., Mahler, S. V., Chi, H. & De Wit, H. (2006). Differential effects of nicotine on alcohol consumption in men and women. *Psychopharmacology*, 186(1), 54. https://doi.org/10.1007/s00213-006-0338-y

Ahmed, F. M. A. & Peeran, S. W. (2016). Significance and determinants of tobacco use: A brief review. *Dentistry and Medical Research*, 4(2), 33. https://doi.org/10.4103/2348-1471.184726

Ahn, N., García, J. R. & Jimeno, J. F. (2004). The impact of unemployment on individual well-being in the EU. European Network of Economic Policy Research Institutes, *Working Paper* N° 29.
https://www.ceps.eu/ceps-publications/impact-unemployment-individual-well-being-eu/

Anderson, P., Cremona, A., Paton, A., Turner, C. & Wallace, P. (1993). The risk of alcohol. *Addiction*, 88(11), 1493–1508. https://doi.org/10.1111/j.1360-0443.1993.tb03135.x

Austin, P. C. (2011). Optimal caliper widths for propensity-score matching when estimating differences in means and differences in proportions in observational studies. *Pharmaceutical Statistics*, 10(2), 150–161.
https://doi.org/10.1002/pst.433

Barnay, T. & Defebvre, É. (2016). L'influence de la santé mentale déclarée sur le maintien en emploi. *Économie et Statistique*, 486-487, 45–78. https://www.insee.fr/fr/statistiques/2110917?sommaire=2110927

Barrett, S. P., Tichauer, M., Leyton, M. & Pihl, R. O. (2006). Nicotine increases alcohol self-administration in non-dependent male smokers. *Drug and Alcohol Dependence*, 81(2), 197–204.
https://doi.org/10.1016/j.drugalcdep.2005.06.009

Bartley, M. & Owen, C. (1996). Relation between socioeconomic status, employment, and health during economic change, 1973-93. *British Medical Journal*, 313(7055), 445–449. https://doi.org/10.1136/bmj.313.7055.445

Baser, O. (2006). Too much ado about propensity score models? Comparing methods of propensity score matching. *Value in Health*, 9(6), 377–385. https://doi.org/10.1111/j.1524-4733.2006.00130.x

Batenburg, M. & Reinken, J. A. (1990). The relationship between sickness absence from work and pattern of cigarette smoking. *The New Zealand Medical Journal*, 103(882), 11–13.
https://europepmc.org/article/med/2360925

Bjartveit, K. & Tverdal, A. (2005). Health consequences of smoking 1–4 cigarettes per day. *Tobacco Control*, 14(5), 315–320. http://dx.doi.org/10.1136/tc.2005.011932

Blasco, S. & Brodaty, T. (2016). Chômage et santé mentale en France. *Économie et Statistique*, 486, 17–44. https://www.insee.fr/fr/statistiques/2110915?sommaire=2110927

Bléhaut, M. & Rathelot, R. (2014). Expérimentation contrôlée contre appariement : le cas d'un dispositif d'accompagnement de jeunes diplômés demandeurs d'emploi. *Économie et prévision*, 204-205, 163–181. https://doi.org/10.3917/ecop.204.0163

Böckerman, P. & Ilmakunnas, P. (2009). Unemployment and self-assessed health: evidence from panel data. *Health Economics*, 18(2), 161–179. https://doi.org/10.1002/hec.1361

Browning, M., Moller Dano, A. & Heinesen, E. (2006). Job displacement and stress-related health outcomes. *Health Economics*, 15(10), 1061–1075. https://doi.org/10.1002/hec.1101

Browning, M. & Heinesen, E. (2012). Effect of job loss due to plant closure on mortality and hospitalization. *Journal of Health Economics*, 31(4), 599–616. https://doi.org/10.1016/j.jhealeco.2012.03.001

Burgard, S. A., Brand, J. E. & House, J. S. (2007). Toward a better estimation of the effect of job loss on health. *Journal of Health and Social Behavior*, 48(4), 369–384. https://doi.org/10.1177/002214650704800403

Burström, B. & Fredlund, P. (2001). Self-rated health: Is it as good a predictor of subsequent mortality among adults in lower as well as in higher social classes? *Journal of Epidemiology & Community Health*, 55(11), 836–840. http://dx.doi.org/10.1136/jech.55.11.836

Caliendo, M. & Kopeinig, S. (2008). Some practical guidance for the implementation of propensity score matching. *Journal of Economic Surveys*, 22(1), 31–72. https://doi.org/10.1111/j.1467-6419.2007.00527.x

Classen, T. J. & Dunn, R. A. (2012). The effect of job loss and unemployment duration on suicide risk in the United States: A new look using mass-layoffs and unemployment duration. *Health Economics*, 21(3), 338–350. https://doi.org/10.1002/hec.1719

Com-Ruelle, L. & Célant, N. (2013). Évolution de la prévalence des différents profils d'alcoolisation chez les adultes en France de 2002 à 2010. *Bulletin épidémiologique hebdomadaire*, 16-17, 18. https://www.santepubliquefrance.fr/determinants-de-sante/alcool/documents/article/evolution-de-la-prevalence-des-differents-profils-d-alcoolisation-chez-les-adultes-en-france-de-2002-a-2010

Connelly, J. E., Philbrick, J. T., Smith Jr, G. R., Kaiser, D. L. & Wymer, A. (1989). Health perceptions of primary care patients and the influence on health care utilization. *Medical Care*, S99-S109. https://doi.org/10.1097/00005650-198903001-00009

Connor, J. (2017). Alcohol consumption as a cause of cancer. *Addiction*, 112(2), 222–228. https://doi.org/10.1111/add.13477

Danaei, G., Ding, E. L., Mozaffarian, D., Taylor, B., Rehm, J., Murray, C. J. & Ezzati, M. (2009). The preventable causes of death in the United States: comparative risk assessment of dietary, lifestyle, and metabolic risk factors. *PLoS Medicine*, 6(4), e1000058. https://doi.org/10.1371/annotation/0ef47acd-9dcc-4296-a897-872d182cde57

De Leon, J., Rendon, D. M., Baca-Garcia, E., Aizpuru, F., Gonzalez-Pinto, A., Anitua, C. & Diaz, F. J. (2007). Association between smoking and alcohol use in the general population: stable and unstable odds ratios across two years in two different countries. *Alcohol and Alcoholism*, 42(3), 252–257. https://doi.org/10.1093/alcalc/agm029

Dee, T. S. (1999). The complementarity of teen smoking and drinking. *Journal of Health Economics*, *18*(6), 769–793. https://doi.org/10.1016/S0167-6296(99)00018-1

Dehejia, R.H. & Wahba, S. (2002). Propensity score-matching methods for non-experimental causal studies. *Review of Economics and Statistics*, 84(1), 151–161. https://doi.org/10.3386/w6829

Edwards, G. (1997). Alcohol policy and the public good. *Addiction*, 92(3s1), 73–80. https://doi.org/10.1111/j.1360-0443.1997.tb03399.x

Falba, T., Teng, H. M., Sindelar, J. L. & Gallo, W. T. (2005). The effect of involuntary job loss on smoking intensity and relapse. *Addiction*, 100(9), 1330–1339. https://doi.org/10.1111/j.1360-0443.2005.01150.x

Falk, D. E., Hsiao-Ye, Y. I. & Hiller-Sturmhöfel, S. (2006). An epidemiologic analysis of co-occurring alcohol and tobacco use and disorders. *Alcohol Research*, 29(3), 162–171. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6527037/

Franks, P., Gold, M. R. & Fiscella, K. (2003). Sociodemographics, self-rated health, and mortality in the US. *Social Science & Medicine*, 56(12), 2505–2514. https://doi.org/10.1016/s0277-9536(02)00281-2

Gathergood, J. (2013). An instrumental variable approach to unemployment, psychological health and social norm effects. *Health Economics*, 22(6), 643–654. https://doi.org/10.1002/hec.2831

Gebel, M. & Voßemer, J. (2014). The impact of employment transitions on health in Germany. A difference-in-differences propensity score matching approach. *Social Science & Medicine*, 108, 128–136. https://doi.org/10.1016/j.socscimed.2014.02.039

Gervais, M., Jaimovich, N., Siu, H. E. & Yedid-Levi, Y. (2016). What should I be when I grow up? Occupations and unemployment over the life cycle. *Journal of Monetary Economics*, 83, 54–70. https://doi.org/10.1016/j.jmoneco.2016.08.003

Grant, M. D., Piotrowski, Z. H. & Chappell, R. (1995). Self-reported health and survival in the Longitudinal Study of Aging, 1984–1986. *Journal of Clinical Epidemiology*, 48(3), 375–387. https://doi.org/10.1016/0895-4356(94)00143-e

Halpern, M. T., Shikiar, R., Rentz, A. M. & Khan, Z. M. (2001). Impact of smoking status on workplace absenteeism and productivity. *Tobacco Control*, 10(3), 233–238. http://dx.doi.org/10.1136/tc.10.3.233

Heckman, J. J., Ichimura, H. & Todd, P. (1998). Matching as an econometric evaluation estimator. *The Review of Economic Studies*, 65(2), 261–294. https://doi.org/10.2307/2971733

Hill, C. (2003). L'augmentation du prix du tabac: une mesure de santé publique. *Bulletin épidémiologique hebdomadaire*, 22-23. http://beh.santepubliquefrance.fr/beh/2003/22_23/beh_22_23_2003.pdf

Hill, C. (2014). Impact de l'augmentation des prix sur la consommation de tabac. Paris: Institut Gustave Roussy. https://www.gustaveroussy.fr/sites/default/files/impact_prix_consommation_tabac_2014.pdf

Ichino, A., Mealli, F. & Nannicini, T. (2008). From temporary help jobs to permanent employment: what can we learn from matching estimators and their sensitivity? *Journal of Applied Econometrics*, 23(3), 305–327. https://doi.org/10.1002/jae.998

Idler, E. L. & Angel, R. J. (1990). Self-rated health and mortality in the NHANES-I Epidemiologic Follow-up Study. *American Journal of Public Health*, 80(4), 446–452. https://doi.org/10.2105/ajph.80.4.446

Idler, E. L. & Benyamini, Y. (1997). Self-rated health and mortality: a review of twenty-seven community studies. *Journal of Health and Social Behavior*, 21–37. https://doi.org/10.2307/2955359

Idler, E. L. & Kasl, S. V. (1995). Self-ratings of health: do they also predict change in functional ability? *The Journals of Gerontology Series B: Psychological Sciences and Social Sciences*, 50(6), S344–S353. https://doi.org/10.1093/geronb/50b.6.s344

Imbens, G. W. & Wooldridge, J. M. (2009). Recent developments in the econometrics of program evaluation. *Journal of Economic Literature*, 47(1), 5–86. https://doi.org/10.3386/w14251

Jarvis, M. J. & Wardle, J. (1999). Social patterning of individual health behaviours: the case of cigarette smoking. *Social Determinants of Health*, 2, 224-37. https://doi.org/10.1093/acprof:oso/9780198565895.003.11

Johansson, E., Alho, H., Kiiskinen, U. & Poikolainen, K. (2007). The association of alcohol dependency with employment probability: evidence from the population survey 'Health 2000 in Finland'. *Health Economics*, 16(7), 739–754. https://doi.org/10.1002/hec.1201

Jusot, F., Khlat, M., Rochereau, T. & Serme, C. (2008). Job loss from poor health, smoking and obesity: a national prospective survey in France. *Journal of Epidemiology & Community Health*, 62(4), 332–337. https://doi.org/10.1136/jech.2007.060772

Kuhn, A., Lalive, R. & Zweimüller, J. (2009). The public health costs of job loss. *Journal of Health Economics*, 28(6), 1099–1115. https://doi.org/10.1016/j.jhealeco.2009.09.004

Lechner, M. (2002). Program heterogeneity and propensity score matching: An application to the evaluation of active labor market policies. *Review of Economics and Statistics*, 84(2), 205–220. https://doi.org/10.1162/003465302317411488

Lee, A. J., Crombie, I. K., Smith, W. C. & Tunstall-Pedoe, H. D. (1991). Cigarette smoking and employment status. *Social Science & Medicine*, 33(11), 1309–1312. https://doi.org/10.1016/0277-9536(91)90080-V

Linn, M. W., Sandifer, R. & Stein, S. (1985). Effects of unemployment on mental and physical health. *American Journal of Public Health*, 75(5), 502–506. https://doi.org/10.2105/ajph.75.5.502

Lundberg, O. & Manderbacka, K. (1996). Assessing reliability of a measure of self-rated health. *Scandinavian Journal of Social Medicine*, 24(3), 218–224. https://doi.org/10.1177/140349489602400314

Ma, J., Siegel, R. L., Jacobs, E. J. & Jemal, A. (2018). Smoking-attributable Mortality by State in 2014, US. *American Journal of Preventive Medicine*, 54(5), 661–670. https://doi.org/10.1016/j.amepre.2018.01.038

MacDonald, Z. & Shields, M. A. (2004). Does problem drinking affect employment? Evidence from England. *Health Economics*, 13(2), 139–155. https://doi.org/10.1002/hec.816

Madden, P. A. & Heath, A. C. (2002). Shared genetic vulnerability in alcohol and cigarette use and dependence. *Alcoholism: Clinical and Experimental Research*, 26(12), 1919–1921. https://doi.org/10.1111/j.1530-0277.2002.tb02503.x

Marcus J (2014). Does Job Loss Make You Smoke and Gain Weight? *Economica*, 81(324), 626–648. https://dx.doi.org/10.2139/ssrn.2020174

McCallum, J., Shadbolt, B. & Wang, D. (1994). Self-rated health and survival: a 7-year follow-up study of Australian elderly. *American Journal of Public Health*, 84(7), 1100–1105. https://doi.org/10.2105/ajph.84.7.1100

McGinnis, J. M. & Foege, W. H. (1993). Actual causes of death in the United States. *Jama*, 270(18), 2207–2212. https://doi.org/10.1001/jama.270.18.2207

Mello, N. K., Mendelson, J. H., & Palmieri, S. L. (1987). Cigarette smoking by women: interactions with alcohol use. *Psychopharmacology*, *93*(1), 8–15. https://doi.org/10.1007/bf02439579

Mintz, J., Boyd, G., Rose, J. E., Charuvastra, V. C. & Jarvik, M. E. (1985). Alcohol increases cigarette smoking: a laboratory demonstration. *Addictive Behaviors*, *10*(3), 203–207. https://doi.org/10.1016/0306-4603(85)90001-2

Miquel, L., Rehm, J., Shield, K. D., Vela, E., Bustins, M., Segura, L., Colom, J., Anderson, P. & Gual, A. (2018). Alcohol, tobacco and health care costs: a population-wide cohort study (n= 606 947 patients) of current drinkers based on medical and administrative health records from Catalonia. *European Journal of Public Health*, 28(4), 674–680. https://doi.org/10.1093/eurpub/ckx236

Mokdad, A. H., Marks, J. S., Stroup, D. F. & Gerberding, J. L. (2004). Actual causes of death in the United States, 2000. *Jama*, 291(10), 1238–1245. https://doi.org/10.1001/jama.291.10.1238

Montgomery, S. M., Cook, D. G., Bartley, M. J. & Wadsworth, M. E. (1998). Unemployment, cigarette smoking, alcohol consumption and body weight in young British men. *European Journal of Public Health*, 8(1), 21–27. http://dx.doi.org/10.1093/eurpub/8.1.21

Morris, J. K., Cook, D. G. & Shaper, A. G. (1992). Non-employment and changes in smoking, drinking, and body weight. *British Medical Journal*, 304(6826), 536–541. https://dx.doi.org/10.1136%2Fbmj.304.6826.536

Mullahy, J. & Sindelar, J. (1996). Employment, unemployment, and problem drinking. *Journal of Health Economics*, 15(4), 409–434. https://doi.org/10.3386/w5123

Nelson, D. E., Jarman, D. W., Rehm, J., Greenfield, T. K., Rey, G., Kerr, W. C., ... & Naimi, T. S. (2013). Alcohol-attributable cancer deaths and years of potential life lost in the United States. *American Journal of Public Health*, 103(4), 641–648. https://dx.doi.org/10.2105%2FAJPH.2012.301199

Norström, T. (2006). Per capita alcohol consumption and sickness absence. *Addiction*, 101(10), 1421–1427. https://doi.org/10.1111/j.1360-0443.2006.01446.x

Okun, M. A., Stock, W. A., Haring, M. J. & Witter, R. A. (1984). Health and subjective well-being: A meta-analyis. *The International Journal of Aging and Human Development*, 19(2), 111–132. https://doi.org/10.2190/QGJN-0N81-5957-HAQD

Osipow, S. H. & Fitzgerald, L. F. (1993). Unemployment and mental health: A neglected relationship. *Applied and Preventive Psychology*, 2(2), 59–63. https://doi.org/10.1016/S0962-1849(05)80112-X

Peck, D. F. & Plant, M. A. (1986). Unemployment and illegal drug use: concordant evidence from a prospective study and national trends. *British Medical Journal* (Clin Res Ed), 293(6552), 929–932. https://dx.doi.org/10.1136%2Fbmj.293.6552.929

Peretti-Watel, P., Constance, J., Seror, V. & Beck, F. (2009). Cigarettes and social differentiation in France: is tobacco use increasingly concentrated among the poor? *Addiction*, 104(10), 1718–1728. https://doi.org/10.1111/j.1360-0443.2009.02682.x

Peto, R., Boreham, J., Lopez, A. D., Thun, M. & Heath, C. (1992). Mortality from tobacco in developed countries: indirect estimation from national vital statistics. *The Lancet*, 339(8804), 1268–1278. https://doi.org/10.1016/0140-6736(92)91600-d

Pirracchio, R., Resche-Rigon, M. & Chevret, S. (2012). Evaluation of the propensity score methods for estimating marginal odds ratios in case of small sample size. *BMC Medical Research Methodology*, 12(1), 70. https://doi.org/10.1186/1471-2288-12-70

Praud, D., Rota, M., Rehm, J., Shield, K., Zatoński, W., Hashibe, M., ... & Boffetta, P. (2016). Cancer incidence and mortality attributable to alcohol consumption. *International Journal of Cancer*, 138(6), 1380–1387. https://doi.org/10.1002/ijc.29890

Rice, N., Carr-Hill, R., Dixon, P., & Sutton, M. (1998). The influence of households on drinking behaviour: a multilevel analysis. *Social Science & Medicine*, 46(8), 971–979. https://doi.org/10.1016/s0277-9536(97)10017-x

Ronchetti, J. & Terriau A. (2020). L'impact du chômage sur l'état de santé. *Revue Économique*, 71(5), 815-839. https://doi.org/10.3917/reco.715.0815

Ronchetti, J. & Terriau A. (2019). Impact of unemployment on self-perceived health: Evidence from French panel data. *The European Journal of Health Economics*, 20(6), 879–889. https://doi.org/10.1007/s10198-019-01050-5

Rosenbaum, P. R. & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70(1), 41–55. https://doi.org/10.1093/biomet/70.1.41

Rosenbaum, P. R. & Rubin, D. B. (1985). The bias due to incomplete matching. *ETS Research Report Series*, 1983 (2), 103–116. https://doi.org/10.1002/j.2330-8516.1983.tb00037.x

Rosenbaum, P.R. & Rubin, D.B. (1985). Constructing a control group using multivariate matched sampling methods that incorporate the propensity score. *The American Statistician*, 39(1), 33–38. https://doi.org/10.2307/2683903

Salm, M. (2009). Does job loss cause ill health? *Health Economics*, 18(9), 1075–1089. https://doi.org/10.1002/hec.1537

Schmitz, H. (2011). Why are the unemployed in worse health? The causal effect of unemployment on health. *Labour Economics*, 18(1), 71–78. https://doi.org/10.1016/j.labeco.2010.08.005

Shiffman, S. & Balabanis, M. (1995). Associations between alcohol and tobacco. *In: Alcohol and tobacco: From basic science to clinical practice*, pp. 17–36. Bethesda, MD: National Institutes of Health, National Institute on Alcohol Abuse and Alcoholism.

Smith, J. A. & Todd, P. E. (2005). Does matching overcome LaLonde's critique of non-experimental estimators? *Journal of Econometrics*, 125(1-2), 305–353. https://doi.org/10.1016/j.jeconom.2004.04.011

Sturm, R. (2002). The effects of obesity, smoking, and drinking on medical problems and costs. *Health Affairs*, 21(2), 245–253. https://doi.org/10.1377/hlthaff.21.2.245

Tauchmann, H., Lenz, S., Requate, T. & Schmidt, C. M. (2013). Tobacco and alcohol: complements or substitutes? *Empirical Economics*, *45*(1), 539–566. https://doi.org/10.1007/s00181-012-0611-3

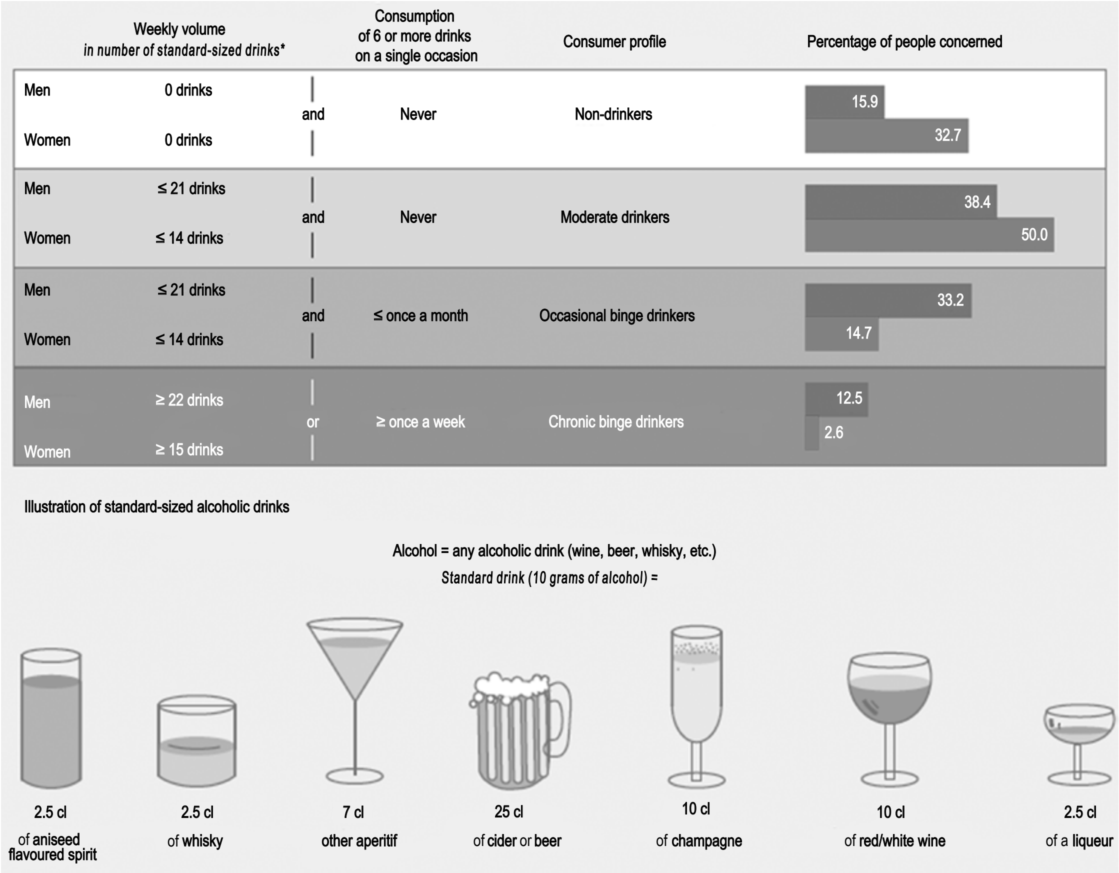
Tefft, N. (2011). Insights on unemployment, unemployment insurance, and mental health. *Journal of Health Economics*, 30(2), 258–264. https://doi.org/10.1016/j.jhealeco.2011.01.006

Thomas, C., Benzeval, M. & Stansfeld, S. A. (2005). Employment transitions and mental health: an analysis from the British household panel survey. *Journal of Epidemiology & Community Health*, 59(3), 243–249. https://dx.doi.org/10.1136%2Fjech.2004.019778

Xu, X., Bishop, E. E., Kennedy, S. M., Simpson, S. A. & Pechacek, T. F. (2015). Annual healthcare spending attributable to cigarette smoking: an update. *American Journal of Preventive Medicine*, 48(3), 326–333. https://doi.org/10.1016/j.amepre.2014.10.012

APPENDIX

Alcohol Consumption Profiles



Sources: Com-Ruelle & Célant (2013).