Social status, life course events and consumption practices: the case of job loss in the French Constances cohort

Marie Plessz

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the case of job loss in the French Constances cohort

Marie Plessz, INRAE, CMH

ESA Consumption conference – Oslo – 2022-09-02

Funded by

IReSP
Institut pour la Recherche en Santé Publique

The question

- How do people change their practices when their socioeconomic position changes?
  - Change in socioeconomic position : job loss
  - Practices: eating, drinking, smoking
- In the literature
  - public-health: little evidence of changes in consumption upon job loss
  - social science: qualitative research, describes practices *in* unemployment

My contribution relies on

- A Weberian perspective on social status
- A praxeological approach to consumption
- Statistical analysis of prospective cohort data

Theoretical framework

- Job loss and weberian theory of class/status
  - Job loss changes class position as a functional position on the labour market
  - Does it lead to a change in social status?
    - Weber: social honor (dignity/respectability). Lifestyle generates honor
  - Do people change their lifestyle upon job loss?
- Theories of practice
  - Lifestyle: a constellation of practices regularly observed together
    - When class position changes, do practices change consistantly enough to say it is a change in lifestyle?
  - I focus on everyday practices for which consumption is central
    - Eating, Drinking, Smoking
  - I capture them through things consumed
    - Vegetables, fish, red meat, fastfood dishes
    - Alcoholic beverages, sweetened drinks
    - Cigarette
  - I focus on how often people consume these things
    - 3-4 categories

Data

Constances: a large epidemiologic cohort in the adult population living in metropolitan France

- Inclusion: 2012-2019
- 200,000 participants aged 18-69 registered in the French general health insurance system (85% of the adults, no self-employed)
- Representative sampling strategy

- Data used
  - At inclusion: Food habits, alcohol, tobacco, socioeconomic situation
  - Follow-up: 2017 follow-up questionnaire

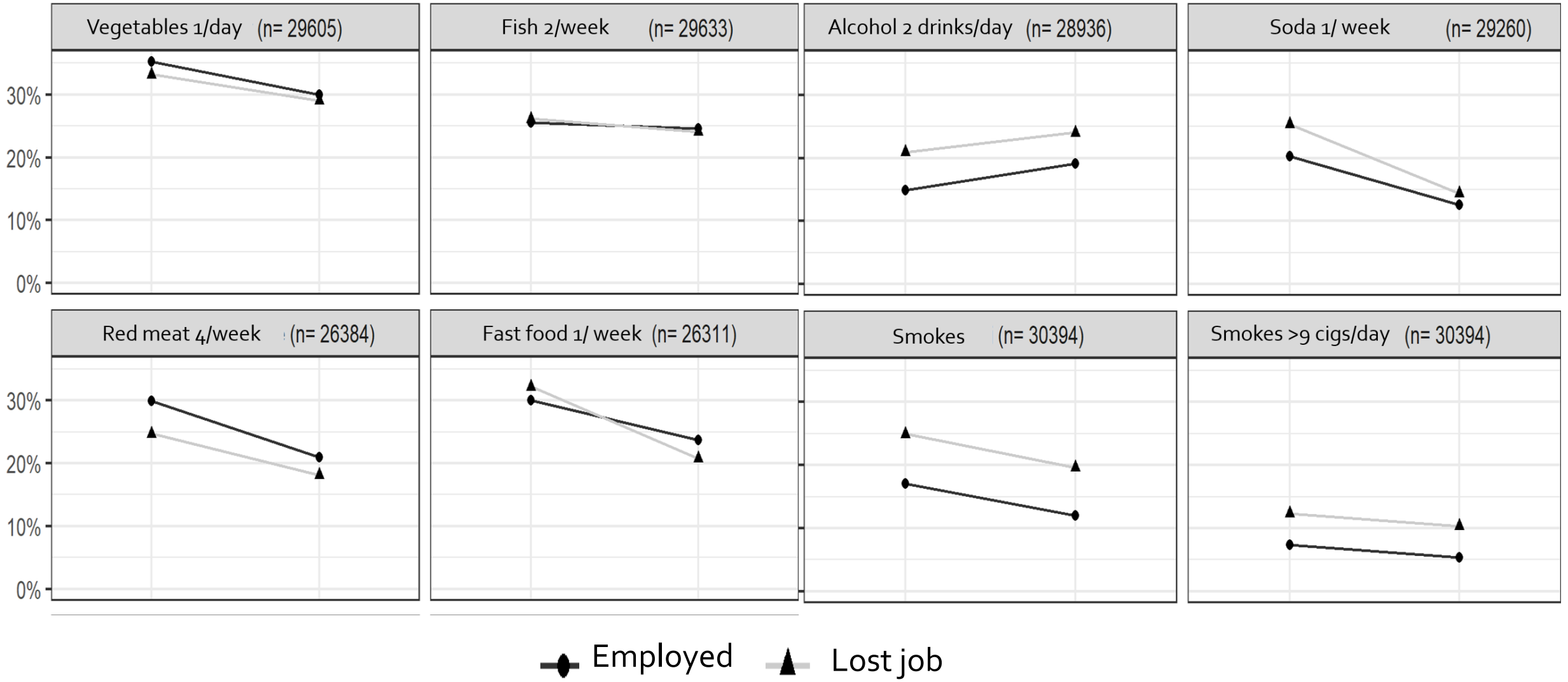
Principal investigators: Marcel Goldeberg, Marie Zins, Lisa Berkman.
CNIL / GDPR-proof (for Constances: N°910486, for Calico: DR-2017-168).
Project calico funded by IRESP.

Analytical strategy

1. Handle the problem like a case-control study
   - Select the **employed** at inclusion, age <60 y, **employed or unemployed in 2017**, no missing data
   - Treatment : job loss.
   - Treated: unemployed in 2017 (**n=718).** Controls: employed in 2017 (n=29,843)
2. Match treated participants with controls who have same characteristics at inclusion
   - Coarsened exact matching (Iacus, King, Porro 2012).
   - Matching variables: dependent variable at inclusion, sex, age groups, partnership status, last job in private sector, financial hardships, ever unemployed, current socioоccupational group , education level, inclusion year [coarsened].
   - At least 502 treated (>82%) were matched.
3. Model the difference-in-difference
   - Ordered logistic regression
   - Cluster-robust standard errors
   - covariates: same as matching (uncoarsened) + geographic area, children in household.

Descriptive statitics:
Caracteristics of the Constances participants employed at inclusion according to status un 2017

Descriptive statitics:
Probability of consuming often each thing, for controls and treated (before matching)

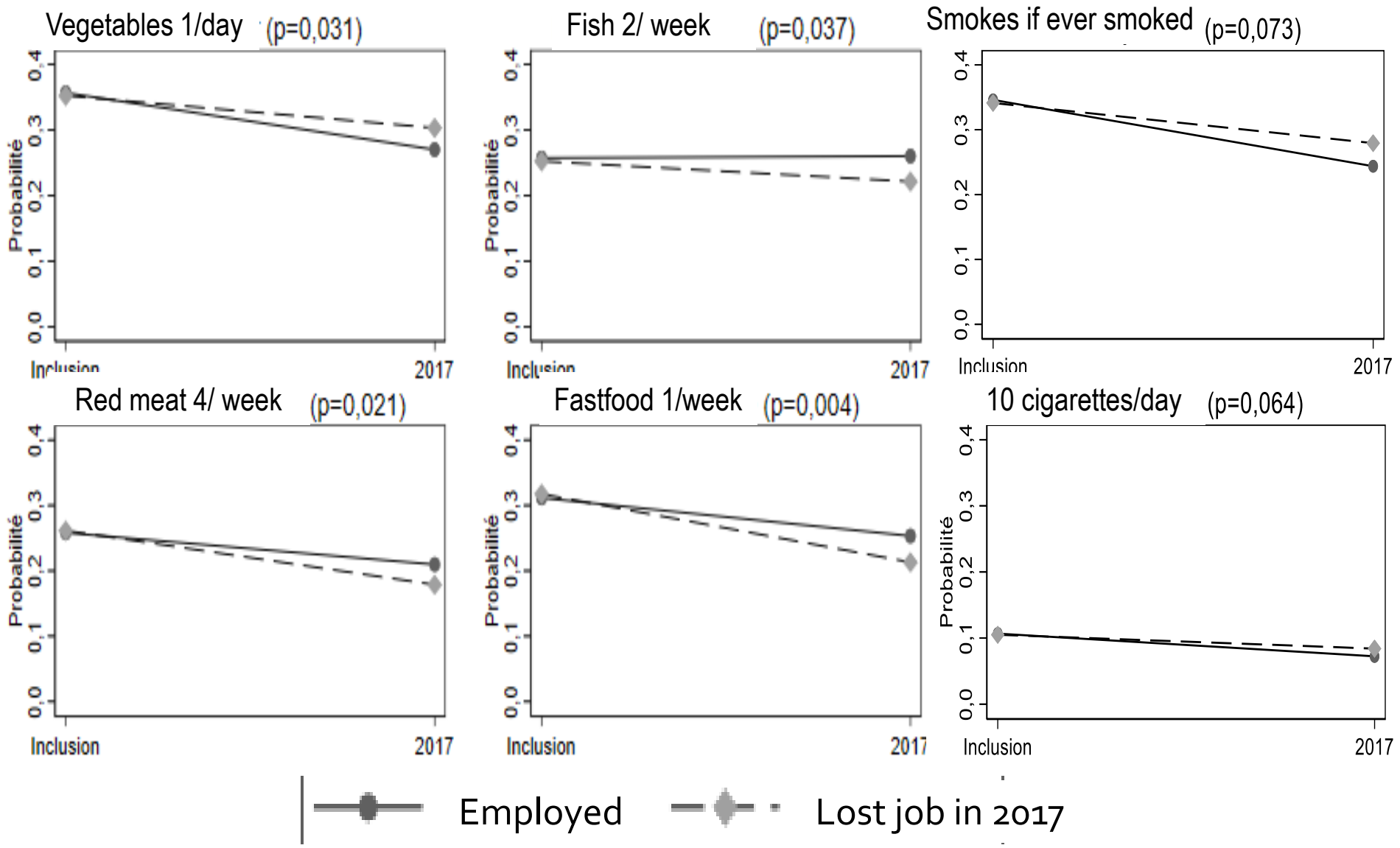


Probability of consuming often each thing for controls and treated, after matching and Difference-in-difference

Dependent variable	DiD coefficient	Change for controls	n	Of which n treated
Vegetables	**0,20**** (0,031)	-0,45*** (0,000)	14 152	573
Fish	**-0,20**** (0,037)	0,02 (0,719)	13 484	578
Red meat	**-0,22**** (0,021)	-0,28*** (0,000)	11 586	508
Fastfood	**-0,28***** (0,004)	-0,33*** (0,000)	13 528	535
Soda	-0,02 (0,882)	-0,63*** (0,000)	17 114	611
Alcohol	0,04 (0,609)	0,17*** (0,000)	13 538	585
Cigarette	**0,19* (0,064)**	-0,45*** (0,000)	15 978	595
Smoker (if ever smoked)	**0,23* (0,073)**	-0,56*** (0,000)	7 378	573

Change for controls : slope for those who remained employed
DiD coefficient: difference in slope for the treated (job loss). If not significant: same slope.

Predicted probabilities of consuming often each thing for controls and treated, after matching and Diff-in-diff



Conclusion

- Maintaining lifestyle = changing practices
  - Different practices are « honorable » according to age (and gender)
  - We are constantly adopting, altering, giving up practices
  - Changes upon job loss cannot be seen as a change in lifestyle
- Consumption as a linkage between class and status
  - Status (honor) relies on practices
  - Consumption is a step in many practices (incl. avoiding consumption of…)
  - Class position on the labour market provides key ressources for consumption

Thank you

gitlab repository: https://al-dev.versailles-grignon.inra.fr/cmh/2020-hdr6

Marie.plessz@inrae.fr

Question on employment status

1. *Quelle est votre situation* ***actuelle*** *vis-à-vis de l'emploi ? (plusieurs réponses possibles)*

☐ 1 Occupe un emploi, y compris si vous êtes temporairement en arrêt de travail (arrêt maladie, congé sans solde ou disponibilité, congé maternité/paternité/d'adoption/parental)

☐ 1 Demandeur d'emploi ou à la recherche d'un emploi

☐ 1 Retraité(e) ou retiré(e) des affaires

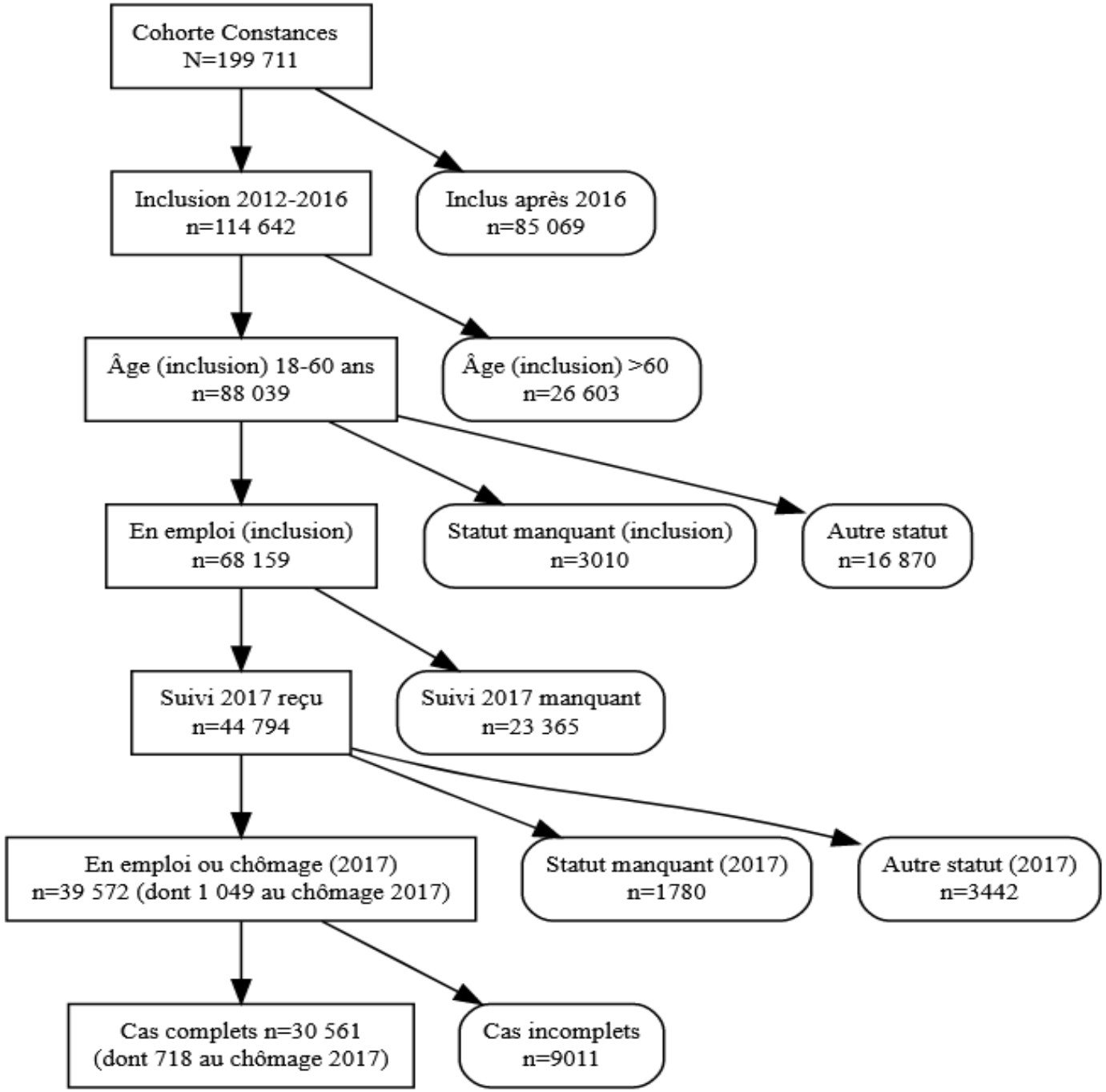
☐ 1 En formation (lycéen(ne), étudiant(e), stagiaire, apprenti(e)...)

☐ 1 Ne travaille pas pour raison de santé (invalidité, maladie chronique...)

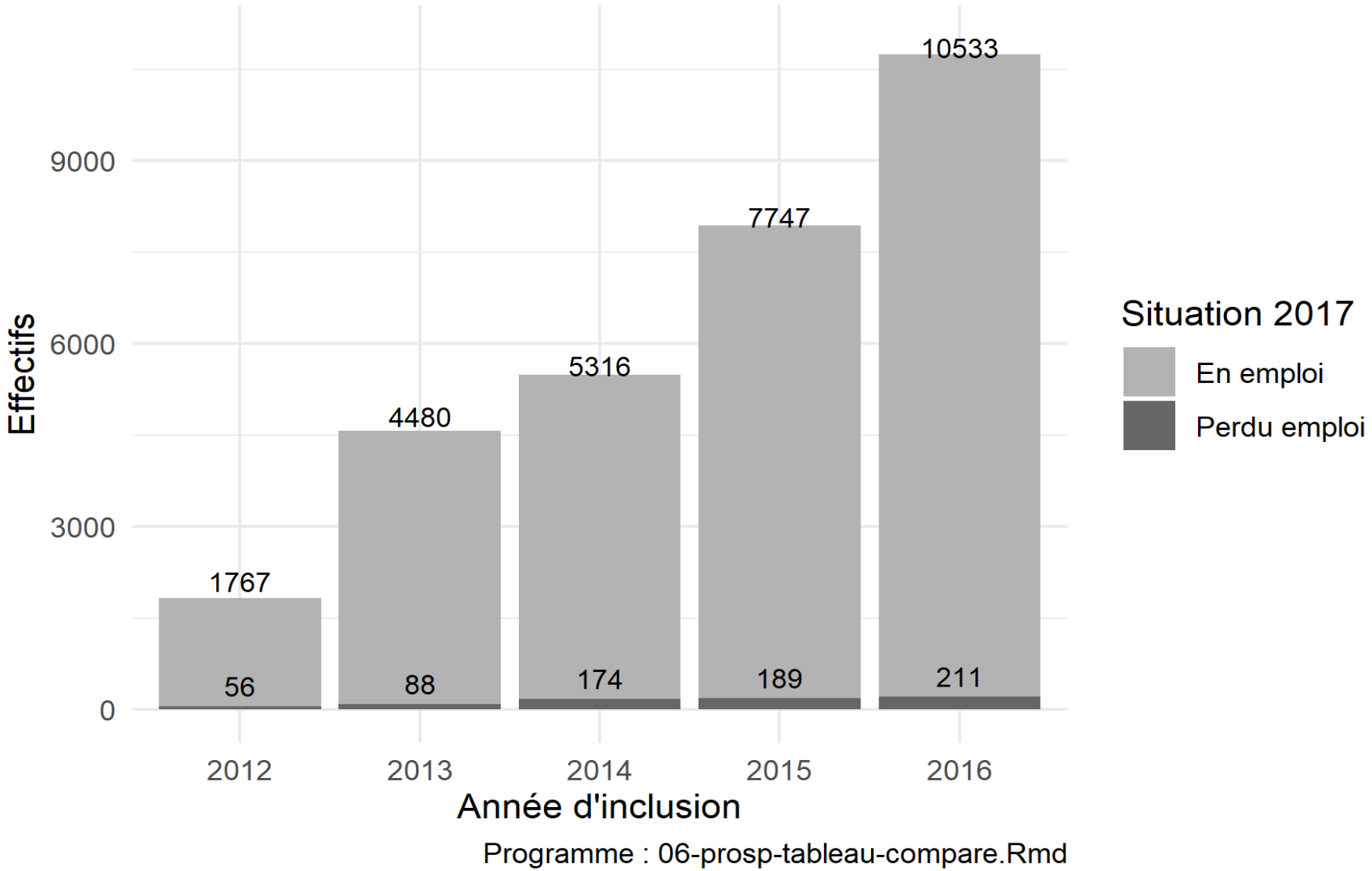
☐ 1 Sans activité professionnelle

☐ 1 Autre, précisez :

Study population: flowchart



Year of inclusion for the study population



Characteristics at inclusion	Employment status 2017	
	Employed (N = 29843)	Unemployed (N = 718)
Male	47,5 %	44,3 %
Lives with partner	79,3 %	64,9 %
18-29 years old	10,1 %	20,8 %
Education < Bac	13,3 %	18,8 %
Current or longest occ. group		
Routine non manual	20,5 %	33,1 %
Routine manual	6,0 %	10,3 %
Private sector	49,6 %	86,1 %
Financial hardships	7,7 %	16,0 %
Career breaks <-> unempl.	13,7 %	28,1 %
Career breaks <-> health	3,2 %	5,8 %
Physical strain work(max=14)	3,52 (3,14)	3,99 (3,65)

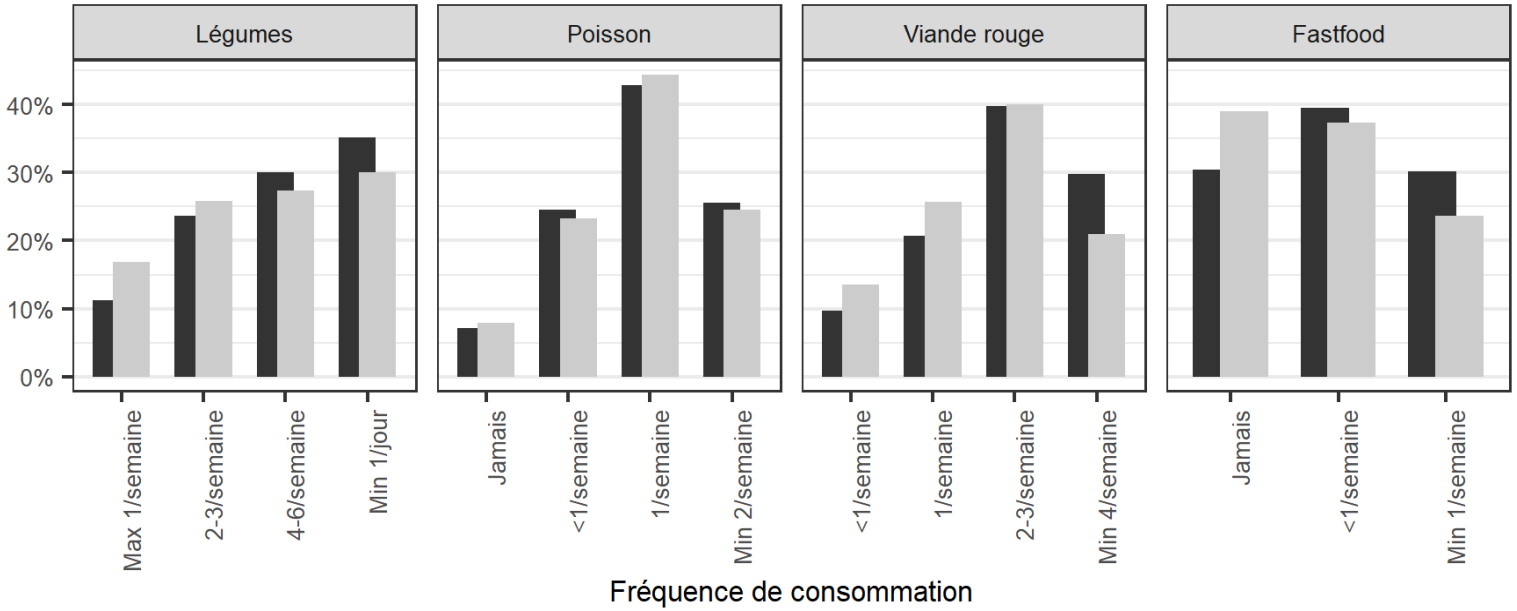
Matching techniques

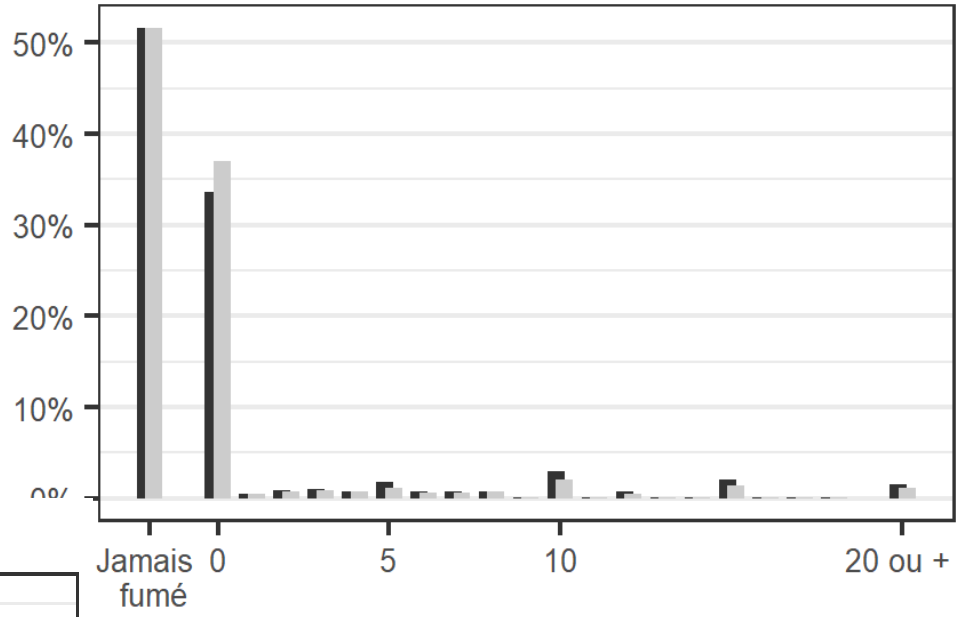
Technique	Despcription	Strengths	Limitations
Exact matching	Find control with exact same characteristics	Distribution of matching variables exactly similar	Hard to find exact match, esp. For continuous variables (age)
Propensity score matching	Find control with same probability of being treated	Works with relatively small pool of controls, even with a lot of variables	Distribution of matching variables may remain different, What is the acceptable level?
Coarsened exact matching (CEM)	Same as exact matching, but researcher can coarsened the coding of specific variables	Allows researcher to choose on which vars matching must be exact, on which it is less. Level of heterogeneity is chosen ex ante.	Requires a large pool of controls esp. If a many matching variables

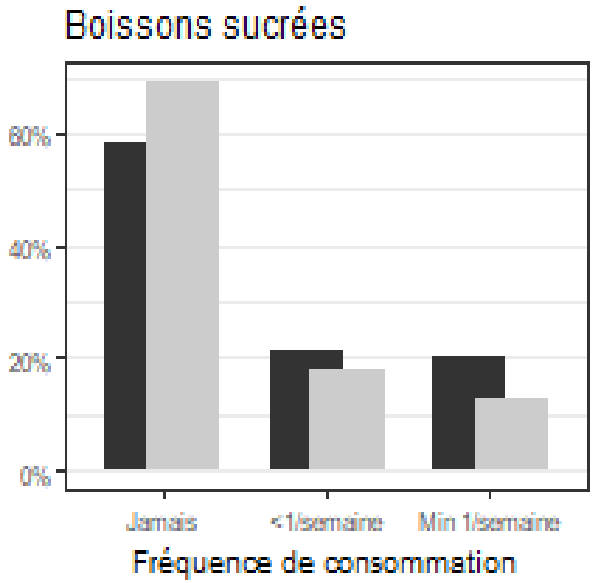
Matching

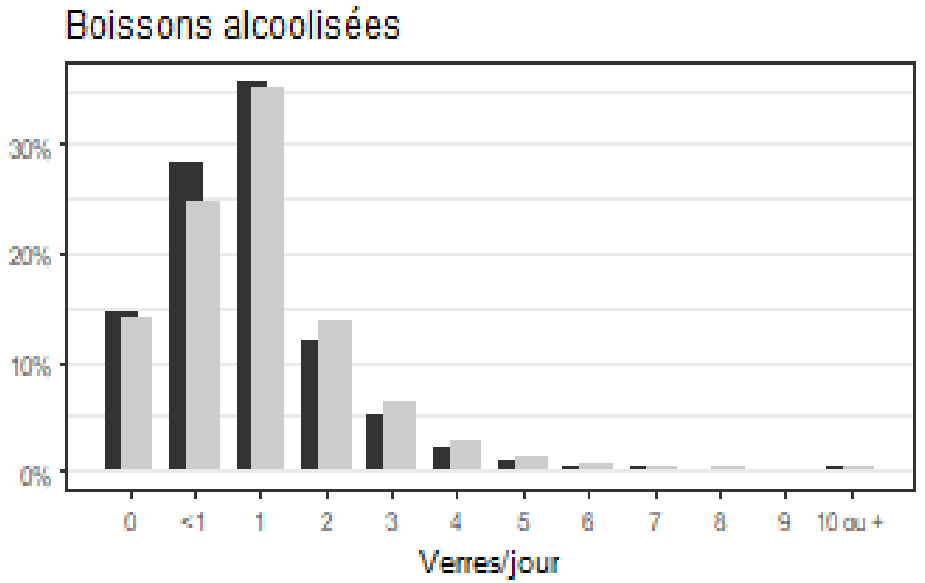
	Cases (unemployed 2017)		Controls (employed 2017)	
Variable	Complete	Matched	Complete	Matched
Vegetables	696	573 (82,3 %)	28 909	6503 (22,5 %)
Fish	693	578 (83,4 %)	28 940	6164 (21,3 %)
Red meat	623	508 (81,5 %)	25 761	5285 (20,5 %)
Fastfood	621	535 (86,2 %)	25 690	6229 (24,2 %)
Soda	687	611 (88,9 %)	28 573	7946 (27,8 %)
Alcohol	703	585 (83,2 %)	29 565	6184 (20,9 %)
Cigarette	714	595 (83,3 %)	29 680	7394 (24,9 %)

Complete: complete cases (no missing value) included in the study sample.


Légumes
Poisson
Viande rouge
Fastfood
40%
30%
20%
10%
0%
Max 1/semaine
2-3/semaine
4-6/semaine
Min 1/jour
Jamais
<1/semaine
1/semaine
Min 2/semaine
<1/semaine
1/semaine
2-3/semaine
Min 4/semaine
Jamais
<1/semaine
Min 1/semaine
Fréquence de consommation


50%
40%
30%
20%
10%
Jamais fumé
0
5
10
20 ou +
Cigarettes/jour


Boissons sucrées
60%
40%
20%
0%
Jamais
<1/semaine
Min 1/semaine
Fréquence de consommation


Boissons alcoolisées
30%
20%
10%
0%
0
<1
1
2
3
4
5
6
7
8
9
10 ou +
Verres/jour


Inclusion
2017