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2025-38 Document de Travail/ Working Paper

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Abstract: How can individuals who have experienced a shock in their addictive consumption trajectories return to their habitual use? As part of a behavioral economics online survey conducted on a representative sample of the French population, we asked respondents to retrospectively quantify their consumption of tobacco, alcohol, and recreational screen use at three moments: before, during, and after the first Covid-19 lockdown. Using a methodology that controls for inter-individual heterogeneity, we test for the presence of a hysteresis effect, i.e. whether the shocks in use that occurred during the lockdown last beyond the end of it and the return to a more normal life. We find persistent hysteresis for the three addictive goods. Studying this hysteresis effect in relation to time preferences, we find that, for tobacco, present-biased individuals exhibit more hysteresis. This hysteresis insight, related to time preferences, offers valuable perspectives for addiction research and policy design addressing population resilience to shocks.

Keywords: addictive goods; hysteresis; panel data; time preferences; behavioral economics

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1. Introduction

The Covid-19 pandemic prompted numerous countries to enforce lockdowns, ushering in significant transformations in the daily routines of individuals. This upheaval extended to various aspects of health and lifestyle behaviors, with notable impacts on exercise, diet, screen time and substance use. A meta-analysis by Trott et al. (2022) finds that 52% of adults increased their leisure screen time during the pandemic, while 7% decreased it. In a comprehensive review, Marsden et al. (2022) observe that, at an aggregate level, there was minimal change in the overall consumption of opioids, alcohol, cannabis, tobacco, and gambling during the initial phases of the pandemic. However, this generalization conceals the nuanced reality that nearly equal proportions of the population exhibited either an increase or decrease in their substance use. For instance, a study conducted in Germany by Koopmann et al. (2021) reveals that 36% of individuals who consume alcohol increased their alcohol intake during the lockdown, while 21% decreased their consumption. Similarly, in Italy, Carreras et al. (2022) report an uptick in tobacco use for 38% of cigarette smokers, contrasted with a reduction in usage for 23% of them. Despite noteworthy variations based on the type of substance, geographic location, and demographic characteristics, a wealth of evidence indicates that a substantial portion of consumers adjusted their consumption patterns of addictive goods, either upward or downward.

These shifts in individual behaviors can be elucidated by multiple factors, including alterations in product availability, such as the closure of restaurants and bars, and restrictions on travel leading to a limitation of possible sales outlets. Changes in the contexts of consumption, such as disruptions of coffee breaks at work, family gatherings, and social events, also played a significant role. Additionally, changes in the motivations for substance use are crucial, with coping mechanisms for stress, boredom, loneliness, and anxiety arising from the pandemic and lockdown situations identified as influential drivers (Martínez-Cao et al., 2021).

From a public health perspective, an important question is whether these changes have long lasting effects. This phenomenon can be described as a ‘hysteresis’ effect. The general notion of hysteresis refers to a phenomenon in which the value of a physical property lags behind changes in its original causal determinants (generally exogenous shocks). The term was first coined by Ewing (1882) referring to resistance of magnetic materials to a change in magnetic force. It has since been applied in a variety of contexts and disciplines, including economics, but essentially from a macroeconomic perspective[1], leaving the question of hysteresis in individual consumer behavior unexplored to the best of our knowledge (although there is a

[1] It seems that Georgescu-Roegen (1971) introduced the notion of hysteresis into the field of economics for the study of irreversibility processes. Elster (1976) played a pivotal role in expanding and endorsing the legitimacy of this concept for economists. Subsequently, in the realm of labor economics, Blanchard and Summers (1986) employed this concept when investigating how temporary shocks could yield a lasting impact on employment levels in Europe. More recently, hysteresis effects have been highlighted at the macroeconomic level, in the case of fiscal policies (Engler and Tervala, 2018; Fatas and Summers, 2018), labor market dynamics (Saez et al., 2021; Tafuro, 2024), and monetary policy (Garga and Singh, 2021). Palley (2023) argues for a broader application of this concept in political economy.

large literature on the lasting effect of exogenous shocks on economic preferences, which will be mentioned in the Discussion). The concept of hysteresis seems particularly relevant to the study of addictive behaviors because of their dynamic nature, created by the key mechanisms of reinforcement and tolerance (Turton and Lingford-Hughes, 2024). The Covid-19 outbreak represented a temporary disruption of environmental conditions, which might have induced changes in the dynamics of consumption and thus changes in long-run use levels. Interestingly, the concept of hysteresis can also be seen as opposed to (or symmetrical with) that of resilience, which was much used during the pandemic and refers to the capacity to withstand or recover quickly from difficulties or the ability of a substance or object to spring back into shape. In short, our research question pertains to population resilience to the Covid-19 crisis—or more precisely to one of its key features, the lockdown—(Fontanarosa and Bauchner, 2020), with a specific focus on behaviors that are particularly sensitive to resilience issues, namely the consumption of addictive goods.

To understand the impact of sudden shifts in addictive consumption on long-term usage, it is useful to draw on the microeconomic foundations of addictive behavior. A key framework is Becker and Murphy's (1988) rational addiction model, a dynamic optimization model assuming agents are fully rational and time-consistent, discounting future costs and rewards exponentially. This dynamic utility maximization results in a steady-state consumption level, with addiction considered voluntary. The model emphasizes that long-term rewards from quitting are heavily discounted compared to short-term benefits from addictive consumption, leading rational agents to prefer addiction over quitting. While the discount rate plays a central role in this model, there is limited discussion on the relevance of using a unique and constant time discount rate. Subsequent models of addictive behaviors, influenced by the literature on time inconsistencies in human behavior (Thaler, 1981; Laibson, 1997), incorporate hyperbolic or quasi-hyperbolic discounting. Major applications include models by O'Donoghue and Rabin (1999; 2002), Gruber and Köszegi (2001), and Carrillo (2005). Such an approach is consistent with neurobiological models of addiction, which distinguish between an impulsive system and a reflective system and suggest that addiction reflects an imbalance in activity within these key neural systems that lead to prioritizing the short-term consequences of a decisional option (Noel et al., 2013).

Empirical evidence consistently supports a positive association between addictive behaviors—particularly smoking—and high discounting (MacKillop et al., 2011; Barlow et al., 2017; Harrison et al., 2018). However, the extent to which these patterns reflect specific time discounting biases, such as present-biased preferences, remains a subject of debate. Several studies argue that smokers disproportionately favor immediate gratification, consistent with models of hyperbolic or quasi-hyperbolic discounting (Bickel et al., 1999; Kang & Ikeda, 2014; Chaloupka et al., 2018). Yet, this relationship appears to be heterogeneous. For instance, Harrison et al. (2010) report differences between men and women, while Harrison et al. (2018) suggest that time inconsistency is non-linear with smoking intensity. Conversely, other empirical studies find no evidence of present bias among smokers (Khwaja et al., 2007; Hofmeyr et al., 2017; Piccoli & Tiezzi, 2021) or drug users (Blondel et al., 2007). Our study is in line with this body of work, with one notable difference:

we study the role of time preferences in the management of an exogenous shock (the Covid-19 lockdown) that modifies the consumption of addictive goods. Our hypothesis is that the agents’ psychological profile with respect to time-discounting is a determinant of their ability to regain control of their consumption after a disruption. More specifically, we consider the observation of hysteresis at the individual level as a marker of a loss of control in consumption trajectories following a shock. We aim to test the statistical hypothesis that present-biased individuals, who exhibit a stronger preference for immediate rewards, are more likely to exhibit hysteresis (i.e. loss of control) than other individuals. It is worth noting that this result is also consistent with the predictions of a simple theoretical model based on standard intertemporal consumption trade-offs, augmented with an addiction lag and an exogenous preference shock—used here as a minimal representation of the lockdown shock. The details of this model are presented in Appendix A1.

The analysis is conducted in two phases, reflecting the two main contributions of this work. In the first phase, we formulate an econometric approach designed to test the presence of a hysteresis effect. This involves examining whether disruptions during the lockdown, such as breaks in the consumption trajectories of three distinct 'goods' (namely, tobacco, alcohol, and leisure screen use), impact post-crisis consumption patterns. Our methodology incorporates individual consumption data referring to three crucial points in time—before, during, and after the lockdown—while considering the inherent dynamics of individuals' consumption behaviors. In the second phase, we relate agents’ addictive consumption trajectories with their unique time-discounting patterns. Using the Convex Time Budget method (Andreoni and Sprenger, 2012) to unveil time preferences, we are able to assign a measure of time inconsistency to each individual, either categorically (distinguishing three groups: present-biased, time-consistent, and future-biased) or in terms of intensity (from strongly present-biased for high negative values to strongly future-biased for high positive values).

Our main finding underscores the presence of hysteresis in all three addictive goods studied. Interestingly, in the case of tobacco, this phenomenon varies in intensity depending on the individual's time preference: smokers with a present bias exhibit the most pronounced hysteresis trap, while future biased smokers tend to avoid it. The data and the empirical approach are described in section 2. Section 3 displays the results and section 4 provides a discussion.

2. Method: data and empirical approach

2.1. Data

We conducted an online survey on a representative sample of the French population[2]. The study protocol was reviewed and authorized by the ethics committee of Aix-Marseille

[2] Note that this survey was part of a more general research project on the study of risk, time and social preferences during and after the Covid-19 crisis. The following papers use some parts of the same dataset: Blayac et al. (2022a) and Rafaï et al. (2023). However, this article is the first to use data collected on addictive behaviors.

University in June 2021 (authorization n°2021-06-03-04). Viavoice, the survey institute, recruited participants using a quota method[3]. A total of 7500 people were contacted, 1154 by telephone and 6346 by email. The telephone was used to make a special effort to recruit people who had participated in a previous wave of the survey[4]. The telephone response rate was 32.1% (338/1154) and the email response rate was 11.0% (700/6346). Overall, 1038 respondents completed the online survey with a signed informed consent form (overall response rate: 13.8%). The responses were collected between August 24, 2021, and October 11, 2021.

We documented the self-reported consumption of three addictive goods—tobacco, alcohol, and leisure screen use—retrospectively at three time points: before the lockdown (January 2020) (t0), during the lockdown (May 2020[5]) (t1), and after the lockdown (September 2021) (t2). Respondents reported quantities consumed, using an anti-chronological order (i.e. starting with their current consumption at the time of the survey in September 2021, then recalling their consumption in May 2020, and finally their consumption in January 2020) and their preferred scale (quantity per day, per week, or per month). They could visualize and modify their responses on a graph. They were also asked how confident in their answers they were[6].

The survey also included a behavioral economics module designed with incentive-compatible tasks. Specifically, we implemented a mini version of the Convex Time Budget (CTB) task (Andreoni and Sprenger, 2012) to assess participants' time preferences. In this task, participants were presented with two screens—corresponding to two scenarios—, each asking them to allocate €40 between two future dates[7]. We applied two different settings based on the response date. For participants who responded on or before September 19, scenario 1 allocations were set between September 30, 2021, and October 30, 2021, while scenario 2 allocations were between October 30, 2021, and November 30, 2021. For those who responded from September 20 onward, scenario 1 allocations were between October 15, 2021, and November 15, 2021, and scenario 2 allocations were between November 15, 2021, and

[3] This approach ensured that the sample was representative of the French population in terms of gender, age, socio-professional category, and region of residence.
[4] See e.g. Blayac et al. (2020b).
[5] The first lockdown in France took place from March 17 to May 11, 2020. Mentioning the month of May may seem ambiguous as a reference point for the lockdown. There are two reasons for this: i) we wanted to capture the highest effect of the lockdown on consumption, which is more likely to occur at the end of the shock than at the beginning, and ii) we wanted to be able to combine the data from this survey with those from a previous survey conducted in May 2020. The coincidence of the dates was important from a methodological point of view, even if we do not take advantage of this possibility in this study on addiction. Finally, we are confident that there was no ambiguity in our wording, which was as follows: "in May 2020, during the first lockdown, [how much did you consume]?".
[6] See Part 3 of the complete questionnaire of our survey in the online Appendix (pp.27-37).
[7] See Task 4 of Part 2 of the complete questionnaire of our survey in the online Appendix (pp.22-24). Conducting the experiment online differs from the controlled lab environment in which the task is usually performed. In our case, this choice is justified by the sanitary context and the desire to have a representative sample of the French population. Several studies have shown that online experiments and lab experiments tend to elicit consistent preferences (e.g. Snowberg & Yariv, 2021; Prissé & Jorrat, 2022).

December 15, 2021. Both scenarios maintained a one-month interval between the options, allowing us to analyze participants' time preference biases.

The value of €1 invested on the first date remained unchanged, while €1 invested on the second date increased to €1.20, i.e. a 20% interest rate. The discount rate choice prioritizes budget balancing over two days a month apart rather than a real-world scenario. It aligns with Andreoni & Sprenger (2012), who varied annual interest rates between 0 and 1000. Participants utilized a slider on the screen, with the flexibility to allocate funds in €1 increments between these extremes. The program instantly calculated potential earnings for the first date (€1 per euro invested) and the second date (€1.20 per euro invested).

We used a standard random payment method. The participants were informed that if they were selected for payment and if the CTB task was chosen for payment, one of the two scenarios would be randomly selected—each with equal probability. The selected scenario determined the actual payment, with the corresponding payouts occurring at either the sooner or later date, depending on the budget allocation chosen by the respondent. Several papers showed that the random payment method is incentive compatible and does not alter the respondent's true preferences (e.g. Starmer & Sugden, 1991, Cubitt et al., 1998, Clot et al., 2018). The average payoff in the CTB task was €44.2 (min: €40; max: €48).

Using the amounts assigned to the first date in each scenario (variable X1 for the first scenario and variable X2 for the second scenario), we created two variables, one categorical and one continuous. For the categorical one, participants were considered time consistent if they chose the same amount (X1=X2), future-biased if they preferred a higher amount in the second scenario (X2>X1), and present-biased if they preferred a higher amount in the first scenario (X1>X2). For the continuous variable, we simply use the difference X2-X1. A high negative value (maximum -40) represents a strong present-bias. A high positive value (maximum +40) represents a strong future-bias.

Note that our implementation of the CTB method presents two potential issues: the inclusion of a front-end delay and the limitation to only two budget allocations (two scenarios). Regarding the first issue, both scenarios incorporated an initial delay, which, based on findings by Balakrishnan et al. (2020) and Imai et al. (2021), may reduce the likelihood of present bias: while present bias remains significant, it appears attenuated when a front-end delay is applied. We elaborate on this point in the Discussion. Second, using only two questions may seem restrictive to measure time preferences. This is the minimum to infer the two individual parameters beta/gamma which describe the quasi-hyperbolic utility function. However, since our objective is not to produce a structural estimate of individuals' present bias, these two questions are sufficient to categorize participants as either present-biased, future-biased, or time-consistent.

Finally, the survey gathered socio-demographic data (gender, age, professional status, monthly income, higher degree) and lockdown-related details (number of rooms and people at home during lockdown). Participants also reported the frequency of feeling bored, lonely, and sad in the past year, which was condensed into a single variable named 'negative feelings.'

This variable was derived from the first eigenvector of a principal component analysis, capturing 70% of the variance in the three emotions.

2.2. Empirical test of hysteresis: a panel data approach

We consider the following dynamic panel data model to study the persistence or the state dependence in individual behaviors:

$$y_{it} = \rho y_{i,t-1} + \gamma X_{it} + \mu_i + \varepsilon_{it}, \qquad t = 0,1,\dots,T \tag{1}$$

where y_{it} corresponds to the quantity consumed.

The model includes control factors X_{it}, individual-specific effects μ_i, and the usual regression error ε_{it}. The inherent dynamic nature of the model implies potential regressor endogeneity, as both the error terms (μ_i and ε_{it}) may exhibit correlation with $y_{i,t-1}$ and X_{it}. This introduces complexity in model estimation, and using a GMM estimator could result in a notable loss of power due to the reliance on numerous instruments. To strike a balance, we adopt a middle-ground approach. Following Mundlak (1978) and Wooldridge (2005, 2019), we opt for a sufficiently flexible specification involving random effects (μ_i) and idiosyncratic error (ε_{it}), acknowledging a correlated random effects model. This choice is made under the assumption that:

$$\mu_i | y_{i,0}, y_{i,1}, Z_i \sim N(\alpha_0 + \alpha_1 y_{i,0} + \alpha_2 y_{i,0} y_{i,1} + Z_i' \vartheta, \sigma_\mu^2) \tag{2}$$

or equivalently,

$$\mu_i = \alpha_0 + \alpha_1 y_{i,0} + \alpha_2 y_{i,0} y_{i,1} + Z_i' \vartheta + u_i, \qquad u_i \sim N(0, \sigma_\mu^2) \tag{3}$$

where $y_{i,0}$ is the initial observation of the dependent variable. This assumption is broad, positing that individual effects hinge on the initial consumption decision ($y_{i,0}$), the cross-effect between consumptions in the first two periods, and time-invariant variables (Z_i), which encompass individual characteristics. By combining both equations, we obtain:

$$y_{it} = \alpha_0 + \alpha_1 y_{i,0} + \alpha_2 y_{i,0} y_{i,1} + \rho y_{i,t-1} + \gamma X_{it} + Z_i' \vartheta + v_{it}, \tag{4}$$

where $v_{it} \equiv (u_i + \varepsilon_{it})$ is the new idiosyncratic regression error term. Estimation of this model can be performed by using standard panel random-effects regression.

For our dataset spanning three periods (t=t0, t1, t2), the model simplifies to a single equation to be estimated:

$$y_{i,t2} = \alpha_0 + \alpha_1 y_{i,t0} + \alpha_2 y_{i,t0} y_{i,t1} + \rho y_{i,t1} + \gamma X_{i,t2} + Z_i' \vartheta + v_{i,t2}. \tag{5}$$

Note that ρ is identifiable up to an additive constant. If there were an additional term, like $\alpha_3 y_{i,1}$, in the distributional assumption (as seen in $\mu_i | y_{i,0}, y_{i,1}, Z_i$ above), it would result in $(\rho + \alpha_3) y_{i,1}$ in the estimated equation. In this case, for identification purposes, we have to impose α_3=0. Ultimately, the persistent or hysteresis effect is expressed as $\frac{\partial y_{i,t2}}{\partial y_{i,t1}} = \rho + \alpha_2 y_{i,t0}$. We observe that the hysteresis effect depends on the initial consumption $y_{i,t0}$. The mean value of this effect can be computed using the sample mean of $y_{i,t0}$ (i.e. $\underline{y_{i,t0}}$). In the case of regression using standardized variables, this effect simplifies to $\frac{\partial y_{i,t2}}{\partial y_{i,t1}} = \rho$ (as the mean of standardized $y_{i,t0}$ is 0). Any value of $\frac{\partial y_{i,t2}}{\partial y_{i,t1}}$ significantly greater than zero implies persistence in the change in consumption initiated at time t1 (which can be either a persistent increase or a persistent decrease), which we call 'hysteresis'. Conversely, a value of $\frac{\partial y_{i,t2}}{\partial y_{i,t1}}$ that is not significantly different from zero implies that the change in consumption initiated at time t1 has no effect on consumption at time t2, which we interpret as 'resilience'.

Note that the model above is estimated in two steps: 1) by stratifying our data based on time preference into 3 groups (time-consistent, present biased, and future-biased groups); 2) with using an interaction term reflecting the intensity of the time-bias revealed.

2.3. Link with time preferences

As outlined in the Introduction, we aim to test the hypothesis that present-bias individuals are more prone to experiencing hysteresis than time-consistent and future-biased individuals. In the first step, the empirical test relies on implementing the hysteresis model outlined in the preceding section, with a stratification of our sample based on time preference groups. While it would be intriguing to stratify by both time preference groups and the profile of use change (increase, decrease, or no change) during the lockdown, our sample size is insufficient for this dual stratification. As a compromise, we introduce the use change profile as a control variable. To assess the relevance of stratifying by subsamples based on time preferences, we first plot the estimated coefficients of interest and their 95% confidence intervals. This enables us to confirm the extent to which the results of our analyses are indeed significantly different by time preference group. Additionally, we conduct supplementary analyses to verify that time preferences do not significantly influence the change in consumption during the shock. These results are detailed in Appendix A2.

2.4. Accounting for the intensity of time-inconsistency

In order to take into account the intensity of time-inconsistency, we run equation (5) for the whole sample with an additional interaction variable $y_{i,t1} \times (X_{i2} - X_{i1})$, where X_{i1} and X_{i2} correspond to the investment amounts at the first date that individual *i* made in round 1 and round 2 of the CTB game, respectively. $X_{i2} - X_{i1}$ is then a measure of intensity of time inconsistency while a zero value corresponds to a time consistence behavior.

In this augmented regression, the hysteresis effect becomes $\frac{\partial y_{i,t2}}{\partial y_{i,t1}} = \rho + \alpha_2 y_{i,t0} + \lambda(X2 - X1)$ where λ is the coefficient associated with this interaction variable. The hysteresis effect now depends not only on the initial consumption $y_{i,t0}$, but also on the intensity of time consistency $(X2 - X1)$. The mean hysteresis effect is $\rho + \lambda \cdot \overline{(X2 - X1)}$, where $\overline{(X2 - X1)}$ is the mean of $(X2 - X1)$.

3. Results

Table 1 provides a summary of descriptive statistics for the variables employed in the study. It begins with the main interest variables, namely the consumption of addictive goods and time preferences, followed by a presentation of the control variables.

Table 1. Descriptive Statistics

	%	Mean	Std. dev.	[min ; max]	#Obs
TOBACCO					
Prevalence of smokers	24.0				1,026
Number of cigarettes/day in t0		9.2	7.6	[0 ; 30]	246
Number of cigarettes/day in t1		10.6	8.8	[0 ; 40]	246
Number of cigarettes/day in t2		8.9	7.8	[0 ; 35]	246
Use change during the lockdown					
Decrease	11.0				246
Increase	30.1				246
ALCOHOL					
Prevalence of drinkers	76.4				1,023
Number of drinks/week in t0		6.0	9.4	[0 ; 112.5]	782
Number of drinks/week in t1		6.3	11.0	[0 ; 150]	782
Number of drinks/week in t2		5.5	7.7	[0 ; 60]	782
Use change during the lockdown					
Decrease	21.7				782
Increase	18.8				782
SCREENS					
Prevalence of screen users	100				1,038
Number of hours watched/day in t0		3.2	2.4	[0 ; 24]	1,038
Number of hours watched/day in t1		3.8	3.0	[0 ; 24]	1,038
Number of hours watched/day in t2		3.0	2.0	[0 ; 18]	1,038
Use change during the lockdown					
Decrease	8.1				1,038
Increase	31.4				1,038
TIME PREFERENCES					
Amount invested at the earliest date in the first scenario (X1)		12.5	12.5	[0 ; 40]	1,038
Amount invested at the earliest date in the second scenario (X2)		12.3	12.4	[0 ; 40]	1,038
Present-biased (X1>X2)	23.5				1,038
Time-consistent (X1=X2)	55.5				1,038
Future-biased (X2>X1)	21.0				1,038
Intensity of time-inconsistency (X2-X1)		-0.2	9.0	[-40 ; 40]	1,038
CONTROL VARIABLES					
Female	49.9				1,034
Age]18-35]	22.5				1,038
Age]35-50]	24.7				1,038
Age]50-65]	26.2				1,038
Age 65+	26.6				1,038
Professional status: working	53.4				1,038
Professional status: retired	30.9				1,038
Professional status: other (student, unemployed, housewife, etc.)	15.7				1,038
Monthly income]0-2000]	25.5				965
Monthly income]2000-3000]	21.9				965
Monthly income]3000-4000]	20.5				965
Monthly income 4000+	32.1				965
High school degree	33.7				1,038
Bachelor’s degree	31.0				1,038
Master’s degree	35.3				1,038
Number of rooms in the home		4.5	1.8	[1 ; 10]	1,024

	%	Mean	Std. dev.	[min ; max]	#Obs
Number of people at home during the lockdown		2.8	1.5	[1 ; 11]	1,024
Felt more often bored during last year	48.4				1,038
Felt more often lonely during the last year	53.7				1,038
Felt more often sad during the last year	47.4				1,038

Table 2 displays estimates of the coefficient of interest, $\frac{\partial y_{i,t2}}{\partial y_{i,t1}}$, derived from the regression model outlined in Section 2.2. The regressions utilize standardized variables, categorizing individuals based on their time preferences (present-biased, time-consistent, and future-biased). The use of standardized variables facilitates result comparison across subsamples. The comprehensive results of the regressions, including estimates for all variables, are provided in Appendix A3.

We observe that the coefficient of interest is positive for all goods when considering the full sample. This pattern suggests hysteresis, wherein an increase (or decrease) in consumption during the lockdown is associated with a subsequent increase (or decrease) in consumption after the lockdown (as $\frac{\partial y_{i,t2}}{\partial y_{i,t1}} > 0$). For example, a coefficient of 0.5 (obtained for tobacco) means that an increase (respect. decrease) of one standard deviation in cigarette consumption in t1 (i.e. during the lockdown) raises (respect. lowers) cigarette consumption in t2 by 0.5 standard deviation, all other things being equal.

It is worth noting that present-bias individuals consistently display hysteresis across all goods. This pattern is exclusive to present-biased individuals among smokers. In the case of alcohol use, time-consistent individuals also exhibit hysteresis, while only future-biased individuals display resilience in their consumption. Notably, for screen use, hysteresis is observed across all time preference groups. Regarding intensity, the hysteresis effect is most pronounced among present-biased smokers (1.18).

Figure 1 provides a summary of the estimated values of the slopes $\frac{\partial y_{i,t2}}{\partial y_{i,t1}}$, along with their corresponding regression confidence intervals. A clear pattern emerges for tobacco: present-biased and future-biased individuals show significantly different behaviors, the former being subject to hysteresis in contrast to the latter. For alcohol, one might be tempted to distinguish between time-consistent and present-biased individuals on the one hand (subject to hysteresis), and future-biased individuals on the other (not subject to hysteresis). However, as for screens, the 95% confidence intervals overlap for the three groups, casting doubts on a significantly different behavior according to the time-preference profile. We thus provisionally conclude that there is no link between hysteresis and time preferences for these two goods.

Table 2. Hysteresis Test on the Sample Stratified by Time Preferences (value of $\frac{\partial y_{i,t2}}{\partial y_{i,t1}}$ reported)

	Full sample		Subsample of present-biased individuals		Subsample of time-consistent individuals		Subsample of future-biased individuals	
	Without controls	With controls	Without controls	With controls	Without controls	With controls	Without controls	With controls
Tobacco	0.522***	0.505***	1.177***	1.186***	0.344*	0.334	0.134	-0.388
	(0.148)	(0.166)	(0.164)	(0.235)	(0.185)	(0.226)	(0.222)	(0.279)
#Obs	246	228	60	59	132	118	54	51
R-squared	0.554	0.564	0.714	0.769	0.579	0.618	0.426	0.567
Alcohol	0.684***	0.629***	0.145*	0.170**	0.593**	0.453*	-0.005	-0.063
	(0.146)	(0.142)	(0.076)	(0.070)	(0.214)	(0.207)	(0.186)	(0.186)
#Obs	782	722	178	171	459	418	145	133
R-squared	0.767	0.785	0.946	0.950	0.713	0.740	0.921	0.934
Screens	0.614***	0.559***	0.503**	0.382**	0.546***	0.501***	0.623***	0.473***
	(0.070)	(0.076)	(0.140)	(0.123)	(0.091)	(0.096)	(0.152)	(0.119)
#Obs	1,038	951	244	231	576	523	218	197
R-squared	0.583	0.582	0.572	0.590	0.655	0.674	0.509	0.523

Notes: Standardized coefficients based on regressions where consumption of addictive products (tobacco, alcohol or screens) in t2 is the dependent variable. In the "without controls" regressions, the list of control variables encompasses the use change profile only. For the "with controls" regressions, additional variables include gender, age, professional status, income, degree, number of rooms in the home, number of people at home during the lockdown, and negative feelings during the lockdown (refer to Appendix A3 for complete results). Robust standard errors are presented in parentheses. Significance levels are denoted as ***p<0.01, **p<0.05, *p<0.1.

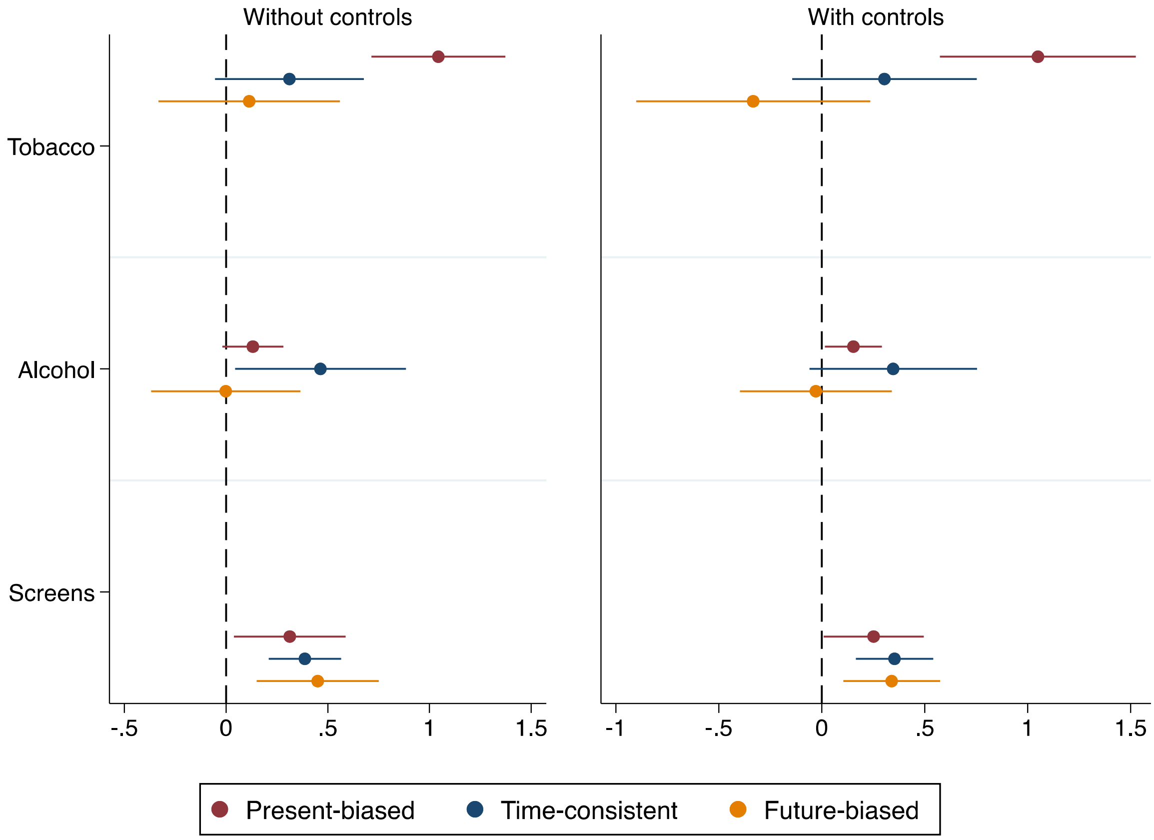

Figure 1. Plot of Estimated Coefficients of Interest and Their 95% Confidence Intervals.

Table 3. Hysteresis Test using the Intensity of Time Inconsistency $(X2 - X1)$

	Tobacco		Alcohol		Screens	
	Without controls	With controls	Without controls	With controls	Without controls	With controls
Use in t1	0.497***	0.456***	0.684***	0.627***	0.614***	0.555***
	(0.137)	(0.154)	(0.147)	(0.144)	(0.070)	(0.076)
Intensity of time inconsistency x use in t1	-0.128**	-0.141***	-0.027	-0.037	0.011	0.036
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
#Obs	246	228	782	722	1,038	951
R-squared	0.570	0.582	0.768	0.786	0.583	0.584

Notes: Standardized coefficients based on regressions where consumption of addictive products (tobacco, alcohol or screens) in t2 is the dependent variable. In the "without controls" regressions, the list of control variables encompasses the use change profile only. For the "with controls" regressions, additional variables include gender, age, professional status, income, degree, number of rooms in the home, number of people at home during the lockdown, and negative feelings during the lockdown (refer to Appendix A4 for complete results). Robust standard errors are presented in parentheses. Significance levels are denoted as ***p<0.01, **p<0.05, *p<0.1.

Table 3 confirms the results formerly obtained by stratification using a new definition of the time-bias (continuous, taking into account intensity): hysteresis on tobacco is sensitive to time-biases, while it is not the case of the other addictive products (for them, hysteresis exists, but is not sensitive to time-biases). This additional analysis provides a clear testing of the significance of the effects. The interaction term is only significant for tobacco when using this continuous definition. For this latter case (tobacco), Figure 2 illustrates the hysteresis effect as a function of the intensity of time inconsistency $\rho + \lambda(X2 - X1)$, based on the results in Table 3, assuming $y_{i,t0} = 0$ (recalling that variables are standardized). The width of the circles represents the concentration/dispersion of data observations. The hysteresis effect is positive for most of the range of the intensity of time inconsistency $X2 - X1$, but tends to zero for (the most) future-bias individuals.

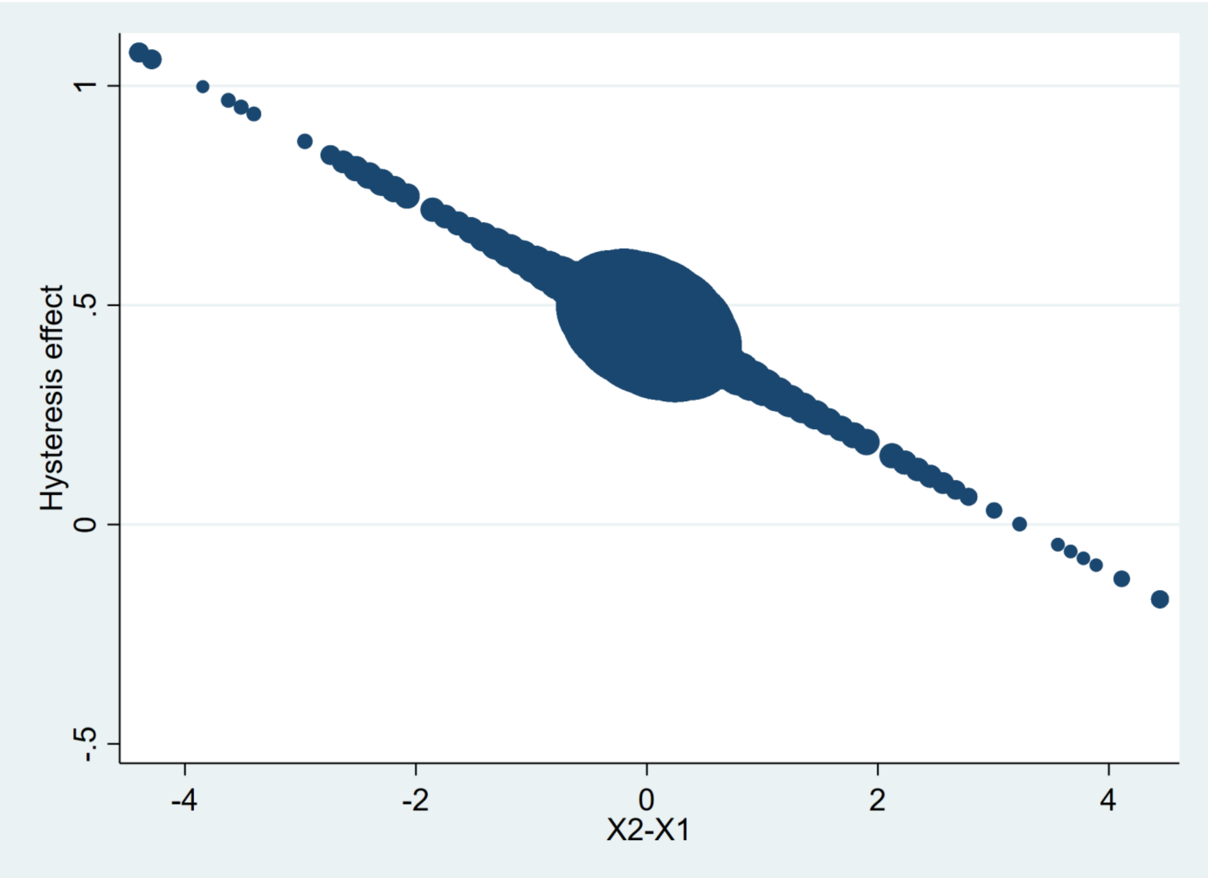

Figure 2. Hysteresis Effect as a Function of the Intensity of Time-Inconsistency for Tobacco.

4. Discussion and conclusion

Our analysis reveals a hysteresis effect for the three tested products, indicating that consumption changes induced by the lockdown shock had a lasting impact, with no return to pre-shock levels even 18 months later. Notably, this hysteresis effect is closely tied to smokers' time preference profiles: only present-biased individuals experience this long-term effect. In contrast, time-consistent and future-biased individuals exhibit resilience and successfully revert to their initial consumption levels. Crucially, our empirical analysis in Appendix 2 demonstrates that time preferences do not determine consumption changes during the lockdown. In particular, present-biased individuals did not adjust their consumption more strongly. This implies that the observed effect does indeed reflect differences in the ability to recover from a shock due to the time preference profile. For alcohol and screen use, the hysteresis effect appears independent of time preferences.

Before delving into theoretical interpretations, it should be noted that this paper contributes to the quite large literature examining the impact of the Covid shock—and often more precisely the impact of one of its key features, the lockdown—on the consumption of addictive goods, notably tobacco, alcohol, and marijuana (e.g. Koopmann et al., 2021; Carreras et al., 2022; Ibarrola-Peña et al., 2022; Sfendla et al., 2022; Vogel et al., 2021; and more specifically for France: Beck et al., 2022; Constant et al., 2020; Rossinot et al., 2020 and Guignard et al., 2021). Some research also targeted digital consumption (Internet, smartphone use, etc.) and reported large significant increases in digital consumption during lockdown (e.g. Bergmann et al., 2022). The novelty of our own approach is that we do not only interrogate the use of the goods at the exact time of the lockdown, but also how these possibly abnormal consumptions during lockdown have impacted patterns of use over a longer period (for 18 months after the first lockdown in France). This is what we call the 'hysteresis' issue. To our knowledge, there is no existing literature about the issue of hysteresis, as applied to addictive goods, yet available.

In a certain way, this paper contributes to the literature on exogenous shocks on economic and social preferences. The impact of exogenous shocks on individuals' preferences and behaviors has been extensively studied by the recent economics literature. In particular, behavioral responses to such shocks have been observed in the aftermath of events like tsunamis (Callen, 2015, Cassar et. al., 2017, Hanaoka et al., 2018, Akesaka, 2019,), typhoons (Eckel et al., 2009, Abatayo & Lynham, 2020), earthquakes (Filipski et al., 2019), floods and draughts (Hill & Viceisza, 2012, Page et al., 2014, Cameron & Shah, 2015, di Falco & Vieider, 2022) but also after conflicts and wars (Voors et al., 2012), financial crises (Malmendier & Nagel, 2011) or multiple shocks (Gloede et al., 2015). In addition, the impact of health crises on individual preferences has come under increased scrutiny following the COVID-19 pandemic (e.g., Schachat et al., 2021, Lohman et al., 2023). However, our study clearly differs from previous research, for two reasons: 1) our outcome variable does not concern preferences themselves, but rather the consequences of preferences (observed one shot) on consumption choices; 2) the universal nature of exposure to the COVID-19 shock requires us to adapt the methods. Unlike those studies, we could not compare a treatment group (exposed to the shock) with a control group (not exposed). Instead, we adopted a partial within-subject design to address the issue of hysteresis in the consumption of addictive products. This specific aspect of our approach is one of the main originalities of our work, as it allows for the identification of hysteresis effects and thus provides an innovative contribution to the literature on shocks.

An important strength of our study is the parallel collection of data on the consumption of addictive goods and of behavioral economics data obtained in an incentive-compatible experimental design. While this is still an empirical consideration, it serves to re-center the focus on the core of the economic theory of addiction: individual time preferences are central to explain addiction behavior. Also, thanks to this combination of data, we believe our study makes a significant contribution to the applied literature on the link between time inconsistency and addictive behaviors. Our results are in line with those of Bickel et al. (1999), Harrison et al. (2010, 2018), Kang & Ikeda (2014) and Chaloupka et al. (2018) emphasizing the link between present-bias preferences and smoking behavior. We add to this literature that time inconsistency seems to be a determining factor in the ability to control consumption trajectories after a shock. This result also serves as an external validation of the Andreoni-Sprenger elicitation method, in the sense that the beta-gamma pairs obtained through the application of the method in the field are effectively associated with real choice behaviors (and hysteresis in them), specifically in the context of tobacco trajectories. The fact that we do not find a similar result for alcohol (hysteresis was found, but it was not related to time preferences) may be due to the fact that alcohol consumption was below addictive levels in our sample (less than one drink per day on average while smokers were smoking 10 cigarettes per day on average). In that case, hysteresis would be explained by other factors, for example catching up on festive events after a period of ban. Recreational screen use also seems to escape the pattern. This could be explained by the fact that trajectories in screen use are more than an individual choice. The Covid-19 crisis has plunged us collectively into a digital world.

In a broader context, our findings underscore the capacity of experimental economics data to enhance our understanding of various health-related choices and behaviors. Time preferences hold particular significance in the health domain, with their role often examined in connection to issues such as dietary habits and their consequences (e.g. obesity) or other preventive behaviors (Volpp, 2015). In this study, we reaffirm the significance of these investigations by situating them within the framework of addictive product consumption trajectories. Through the experimental procedure, we successfully elicited the beta/gamma pair for each individual and established connections with distinct patterns of addictive product consumption. In the case of tobacco, the present-biased individuals succumb to the 'hysteresis trap', while those who are time-consistent or with future-biased inclinations successfully evade it. As each group (present-biased, time-consistent, future-biased) represents a significant proportion of our sample (23.5%, 55.5% and 21% respectively[1]), our results open up two potential policy applications *i)* the systematic profiling of subpopulations particularly exposed to addictive products (e.g. students), by experimental economics tools, may permit the early detection of those the most susceptible to have problems of self-control (present-biased individuals) and those the less (future-biased); ii) then, if individuals' time preferences are malleable, it suggests the potential for manipulation through targeted policies to prevent consistent and present-biased individuals from falling into the hysteresis trap.

This study has some limitations. First, data on consumption are self-reported and based on memories. To check reliability, we asked respondents whether they believed in the global pattern they had reported, for each use of products. Less than 5% (9% for alcohol) say they are not very confident in their answers. Note also that our results are very close to those of Quatremère et al. (2021/2022), who carried out a survey of changes in the consumption of addictive goods in France during lockdown and found that 31.7% of smokers increased their consumption (30.1% in our study), 11.6% decreased their consumption (11.0% in our study), 13.2% of drinkers increased their consumption (18.8% in our study) and 24.1% decreased

[1] These figures are consistent with several other surveys using the Andreoni-Sprenger method to elicit time preferences. See for instance the meta-analysis provided by Imai et al. (2021).

their consumption (21.7% in our study). Of course, this does not rule out the possibility of biases in the responses. It is interesting to note that if the bias were to affect the responses in the sense of smoothing (e.g. to avoid revealing a lack of self-control), this would lead us to underestimate the hysteresis effect. Finally, as the maximum values for alcohol and screen use appear to be very high (150 drinks per week and 24 hours, respectively, which could be suspected of being on the edge of the plausible), we performed a sensitivity analysis by removing the highest consumption values for alcohol and screen use (drinks per week≥75 and daily screen use≥18 hours). The results are reported in Appendix A5 and confirm our previous results: hysteresis exists for these two goods but is not related to time-preferences.

Another limitation may stand in the duration and the nature of the ex-post period (which we named 'long term'). We recognize that the end of the crisis has not really been reached, and that 18 months is a short time to be sure of really talking about the long term. Additionally, we are not sure whether these results are valid in other contexts than the French population. Last, our analyses do not take into account the level of risk associated with the consumption profiles (e.g. a dependence score or a measure of occasional risk taking, such as binge drinking), which is crucial in terms of health consequences and could possibly also play a role in the hysteresis effect.

Regarding our categorization of respondents in terms of their time preference profile, the number of individuals exhibiting present bias is likely underestimated due to the front-end delay included in the CTB questions. This was inevitable, as the online format required the application to remain open for a fixed period, preventing immediate payment and making the front-end delay unavoidable. We also followed closely Andreoni & Sprenger (2012), who incorporated a front-end delay in 30 out of 45 budget allocations to estimate the present bias parameter (β). Including front-end delays is a common approach in this literature (see Cheung, 2015; Cheung et al., 2021, 2022). Estimating the β-δ model using front-end delays, whether in the CTB or MPL method, is therefore a well-established practice. However, front-end delays can significantly reduce estimated present bias (Balakrishnan et al., 2020). Their findings indicate that even a payment at the end of the day, which is common practice, leads to lower present bias compared to truly immediate payment. We therefore conclude that our categorization of present bias likely underestimates the true extent of present bias. To assess whether the possible under-identification of present-biased participants affects our results, we conducted a sensitivity analysis by recoding as present-biased all respondents who scored 0 or 1 on a 0–10 patience scale, indicating extreme impatience. The results remain largely unchanged (see Appendix A6).

To conclude, these results should be considered as a first attempt—opening the issue—for the study on the hysteresis effect in consumption patterns of addictive substances. The notion of hysteresis is a new point that we bring to the public health community and in general to social scientists interested in addictive behaviors: it is relevant for the policy maker as it suggests monitoring and intervening not only on consumption levels of addictive goods, but also on the variations that can occur in period of crisis. In addition, the demonstrated link between revealed time preferences and the resilience capacity of individuals (the other side of hysteresis) confirms the potential of experimental/behavioral economics to better understand human behavior, at least in the specific field of consumption of addictive products.

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Acknowledgements

The ANR (the French national funding agency) provided funding for this research (award number ANR-17-EURE-0020 and ANR-21-COVR-0041). This institution had no role in study design; in the collection, analysis and interpretation of data; in the writing of the articles; and in the decision to submit it for publication.

Ethics

All methods used in this study were carried out in accordance with relevant guidelines and regulations. Informed consent was obtained from all subjects. The ethics committee of Aix-Marseille University reviewed the study protocol in June 2021 and gave the authorization n°2021-06-03-04.

Declaration of Interest

The authors have no competing interests to declare that are relevant to the content of this article.

Data availability

The data used in this study are not publicly available due to anonymity requested by the ethics committee but are available from the corresponding author on reasonable request.

APPENDIX

A1. Addiction and present-bias: a toy-model (3 periods with quadratic utility function)

Assuming a one-good intertemporal choice model, the agent facing an addiction on good y has to manage the following maximization program (maximisation in y_{t1}, y_{t2}, y_{t3}):

$$W(t1) = U(y_{t1}) + \beta.[\gamma U(y_{t2}) + \gamma^2 U(y_{t3})]$$

Function $U(\ y)$ has to be specified. We will use a quadratic form (as for example in Becker and Murphy, 1988), composed of three terms:

$$U(y_{t1}) = b.y_{t1}.\overline{y_{t0}} - c.\frac{1}{2}(\overline{y_{t0}})^2 - a.\frac{1}{2}(y_{t1})^2$$

$b\ (> 0)$ is the direct effect of consumptions, with a dependency to past consumptions; $a\ (> 0)$ is for having a decreasing marginal utility (quadratic); and c (> 0) is a penalty on health (negative effects of past consumption on well-being). Without any budgetary constraint, the program becomes **(Program 1)**:

$$\begin{aligned} W(t1) = \varepsilon.\left(b.y_{t1}.\overline{y_{t0}} - c.\frac{1}{2}(\overline{y_{t0}})^2 - a.\frac{1}{2}(y_{t1})^2\right) \\ + \beta.\gamma\left[b.y_{t2}.y_{t1} - a.\frac{1}{2}(y_{t1})^2 - c.\frac{1}{2}(y_{t2})^2\right] \\ + \gamma^2\left[b.y_{t3}.y_{t2} - a.\frac{1}{2}(y_{t2})^2 - c.\frac{1}{2}(y_{t3})^2\right] \end{aligned}$$

ε will be a preferences-shock parameter, that changes upward in the first period (lockdown: addictive goods are more desired)

<u>**1/ In t1, the agent makes the following choice (**</u>y_{t2}^p and y_{t3}^p are planned levels)

First order conditions for the three derivatives, in y_{t1}, y_{t2}, y_{t3} respectively:

$$\begin{cases} \varepsilon.[b\overline{y_{t0}} - a.y_{t1}] + \beta.\gamma[b.y_{t2}^p - c.y_{t1}] = 0 & (1) \\ \beta.\gamma[b.y_{t1} - a.y_{t2}^p] + \gamma^2[\ b.y_{t3}^p - c.y_{t2}^p] = 0 & (2) \\ b.y_{t2}^p - a.y_{t3}^p = 0 & (3) \end{cases}$$

<u>**2/ In t2, the agents is reassessing his plan, as the factor β is coming again in his intertemporal program**</u>

He faces the following program **(Program 2)**:

$$\begin{aligned} W(t2) = \left[b.y_{t2}.y_{t1} - a.\frac{1}{2}(y_{t1})^2 - c.\frac{1}{2}(y_{t2})^2\right] \\ + \beta.\gamma\left[b.y_{t3}.y_{t2} - a.\frac{1}{2}(y_{t2})^2 - c.\frac{1}{2}(y_{t3})^2\right] \end{aligned}$$

First order conditions for the three derivatives in y_{t2}, y_{t3}:

$$\begin{cases} [b.y_{t1} - a.y_{t2}] + \beta.\gamma[\ b.y_{t3} - c.y_{t2}] = 0 & (4) \\ b.y_{t2} - a.y_{t3} = 0 & (5) \end{cases}$$

3/ Real behavior

Knowing the agent is reconsidering his choice at period t+1, real behaviours will be given by (first equation of program 1 and the two equations of program 2):

$$\varepsilon.[b\overline{y_{t0}} - a.y_{t1}] + \beta.\gamma[b.y_{t2}^{p} - c.y_{t1}] = 0 \quad (1)$$

$$[b.y_{t1} - a.y_{t2}] + \beta.\gamma[\,b.y_{t3} - c.y_{t2}] = 0 \quad (4)$$

$$b.y_{t2} - a.y_{t3} = 0 \quad (5)$$

which give:

$$\varepsilon.[b\overline{y_{t0}} - a.y_{t1}] + \beta.\gamma[b.y_{t2}^{p} - c.y_{t1}] = 0$$

$$[b.y_{t1} - a.y_{t2}] + \beta.\gamma[\,b.\frac{b}{a}y_{t2} - c.y_{t2}] = 0$$

The lockdown can be summarized by a change in preferences ε. In a static comparative exercise, we aim at computing consequential changes in y_{t1} and y_{t2} :

$$\begin{cases} d\varepsilon.(b\overline{y_{t0}} - a.y_{t1}) - \varepsilon.a\,dy_{t1} = \beta.\gamma.[c.dy_{t1} - b.\frac{\partial y_{t2}^{p}}{\partial y_{t1}}.dy_{t1}] \\ b.dy_{t1} = \left[a + \beta.\gamma[\,c - b.\frac{b}{a}]\right] dy_{t2} \end{cases}$$

We obtain:

and

$$\begin{cases} dy_{t1} = \dfrac{b\overline{y_{t0}} - a.y_{t1}}{\beta.\gamma.\left[c - b.\frac{\partial y_{t2}^{p}}{\partial y_{t1}}\right] + \varepsilon.a} d\varepsilon \\ dy_{t2} = \dfrac{b}{\left[a + \beta.\gamma[\,c - b.\frac{b}{a}]\right]}.dy_{t1} \end{cases}$$

Or :

$$\begin{cases} \dfrac{dy_{t2}}{dy_{t1}} = \dfrac{\frac{b}{a}}{\left[1 + \beta.\gamma[\frac{c}{a} - (\frac{b}{a})^2]\right]} \quad (6) \\ \dfrac{dy_{t1}}{d\varepsilon} = \dfrac{b\overline{y_{t0}} - a.y_{t1}}{\beta.\gamma.\left[c - b.\frac{\partial y_{t2}^{p}}{\partial y_{t1}}\right] + \varepsilon.a} d\varepsilon \quad (7) \end{cases}$$

The quantity $\frac{dy_{t2}}{dy_{t1}}$ in *Eq6* is measuring the parameter ρ -factor of hysteresis- used in the econometric modelling.

We obtain the proposition: For all observed shock in y_{t1} (dy_{t1}, given in *Eq5*), the remnant shock in y_{t2} (measured by dy_{t2}) will be moderated by β -present bias.

Proof: Under condition: $\boldsymbol{a.c > b^2}$**, we have:** $\frac{\partial\left(\frac{dy_{t2}}{dy_{t1}}\right)}{\partial\beta} < 0$**. Q.E.D.**

Remark: in this simple model, the other time-preferences parameter γ plays a symmetric role. More general forms of the utility function would probably not produce such a result.

Note (complete solution): The solution of program 1 gives: $y_{t2}^{p} = \frac{1}{1+\frac{\gamma}{\beta}\left[\frac{c}{a}-\left(\frac{b}{a}\right)^2\right]} \cdot \frac{b}{a} \cdot y_{t1}$ and

then we have:

$$y_{t1}^{*} = \varepsilon . \frac{\left[\left(\frac{b}{a}\right)\overline{y_{t-1}}\right]}{\beta . \gamma \left[\frac{\left[\frac{c}{a} - \left(\frac{b}{a}\right)^2\right]\left(1 - \frac{c}{a} . \frac{\gamma}{\beta}\right)}{1 + \frac{\gamma}{\beta}\left[\frac{c}{a} - \left(\frac{b}{a}\right)^2\right]}\right] + \varepsilon}$$

$$y_{t2}^{*} = \varepsilon . \frac{\left[\left(\frac{b}{a}\right)\overline{y_{t-1}}\right]}{\beta . \gamma \left[\frac{\left[\frac{c}{a} - \left(\frac{b}{a}\right)^2\right]\left(1 - \frac{c}{a} . \frac{\gamma}{\beta}\right)}{1 + \frac{\gamma}{\beta}\left[\frac{c}{a} - \left(\frac{b}{a}\right)^2\right]}\right] + \varepsilon} . \frac{\frac{b}{a}}{\left[1 + \beta . \gamma [\frac{c}{a} - \left(\frac{b}{a}\right)^2]\right]}$$

This demonstrates that the condition $a.c > b^2$ allied with $\left(\frac{c}{a} < \frac{\gamma}{\beta}\right)$ is a sufficient condition (but not necessary) to obtain positive levels in. y_{t1} and y_{t2}. At least, this checks that the condition $a.c > b^2$ is not producing inconsistent/degenerated results for the model.

A2. Study of the role of time preferences on use change during the shock

We carry out two types of analysis to check whether time preferences play a role in the change of use during lockdown.

First, we look at the descriptive statistics (see Table A2.1). We find no evidence of a link between initial consumption level (in t0) and time preferences, nor between the change in consumption at the time of the lockdown (change between t0 and t1, studied both in categories and in quantity) and time preferences.

Table A2.1. Descriptive Statistics for the Link between Use Change during the Shock and Time Preferences

	Present-biased	**Time-consistent**	**Future-biased**	
		SMOKERS (N=246)		
N (%) who have decreased use during lockdown	3 (5.0%)	19 (14.4%)	5 (9.3%)	Fisher's exact test: p=0.358
N (%) who have not changed use during lockdown	40 (66.7%)	73 (55.3%)	32 (59.3%)	
N (%) who have increased use during lockdown	17 (28.3%)	40 (30.3%)	17 (31.5%)	
				One-way ANOVA:
Mean of y_0 (std. dev.)	9.8 (8.0)	8.5 (7.3)	10.2 (8.0)	p=0.2949
Mean of $y_1 - y_0$ (std. dev.) *[unit: cigarettes/day]*	1.4 (4.3)	1.3 (4.8)	1.5 (4.1)	p=0.9837
		DRINKERS (N=782)		
N (%) who have decreased use during lockdown	32 (18.0%)	115 (25.0%)	23 (15.9%)	
N (%) who have not changed use during lockdown	107 (60.1%)	267 (58.2%)	91 (62.8%)	Chi2 test: p=0.071
N (%) who have increased use during lockdown	39 (21.9 %)	77 (16.8 %)	31 (21.4%)	
				One-way ANOVA:
Mean of y_0 (std. dev.)	5.6 (7.5)	6.0 (10.0)	6.6 (9.6)	p=0.592
Mean of $y_1 - y_0$ (std. dev.) *[unit: drinks/week]*	0.4 (4.7)	-0.01 (4.3)	1.2 (7.8)	p=0.054
		SCREEN USERS (N=1038)		
N (%) who have decreased use during lockdown	28 (11.5%)	37 (6.4%)	19 (8.7%)	
N (%) who have not changed use during lockdown	1142 (58.2%)	356 (61.8%)	130 (59.6%)	Chi2 test: p=0.195
N (%) who have increased use during lockdown	74 (30.3%)	183 (31.8%)	69 (31.7%)	
				One-way ANOVA:
Mean of y_0 (std. dev.)	3.3 (2.4)	3.2 (2.3)	3.1 (2.6)	p=0.8027
Mean of $y_1 - y_0$ (std. dev.) *[unit: hours/day]*	0.5 (1.7)	0.7 (1.9)	0.6 (1.7)	p=0.2743

Second, we implement Heckman two-stage self-selection models in which the first stage explains the behavioral response to the shock (use increase or decrease) and the second stage implements our hysteresis model. The results are reported in Table A2.2. We find that the inverse mills ratio is usually not significant, implying that the two-stage approach is not relevant. Importantly, time preferences are usually not a determinant of change in use during the lockdown. Age and experiencing negative feelings at this moment seem to be the most important explanatory factors.

Table A2.2. Heckman Two-Stage Regression Results

	Tobacco		Alcohol		Screen Use	
	Decrease	Increase	Decrease	Increase	Decrease	Increase
EQUATION OF INTEREST (dep. var.: use in t2)						
Use in t0	0.936***	-0.259	0.528***	0.999**	0.415***	0.516***
	(0.235)	(0.298)	(0.195)	(0.505)	(0.128)	(0.121)
Use in t1	0.718	0.591***	0.490	-0.010	0.402***	0.312***
	(0.523)	(0.196)	(0.463)	(0.181)	(0.077)	(0.068)
Use in t0 x use in t1	-0.002	0.000	-0.002	-0.001	-0.025	-0.015
	(0.001)	(0.000)	(0.004)	(0.002)	(0.021)	(0.009)
Future-biased	-22.776	-8.240	-2.118	-2.011	-0.195	0.134
	(86.611)	(58.928)	(3.334)	(3.663)	(0.287)	(0.299)
Present-biased	29.476	11.937	-2.997	-0.283	0.098	0.046
	(83.786)	(41.794)	(2.650)	(2.888)	(0.294)	(0.198)
Constant	60.305	-180.245	0.461	-4.154	-0.695	0.473
	(134.833)	(112.598)	(5.869)	(11.956)	(0.709)	(0.390)
FIRST STAGE (dep. var.: change in use during lockdown)						
Female	0.095	-0.034	0.005	0.029	0.292***	0.332***
	(0.242)	(0.146)	(0.096)	(0.100)	(0.111)	(0.104)
Age]35-50]	-0.349	0.173	-0.464***	0.287**	-0.132	-0.240
	(0.335)	(0.186)	(0.161)	(0.137)	(0.177)	(0.151)
Age]50-65]	-0.339	-0.298	-0.489***	-0.132	-0.316*	-0.169
	(1.348)	(0.253)	(0.145)	(0.183)	(0.183)	(0.160)
Age 65+	-0.215	-0.887	-0.830***	-0.389	0.117	-0.874***
	(7.090)	(1.199)	(0.258)	(0.285)	(0.290)	(0.228)
Professional status:	-0.467*	0.134	-0.167	0.034	0.391**	0.140
working	(0.268)	(0.249)	(0.151)	(0.152)	(0.166)	(0.147)
Professional status: retired	-0.720	0.056	-0.155	0.111	-0.224	0.249
	(1.846)	(0.365)	(0.233)	(0.245)	(0.277)	(0.211)
Monthly income	-0.448	0.054	0.112	0.012	-0.077	0.062
]2000-3000]	(7.723)	(0.207)	(0.133)	(0.167)	(0.166)	(0.137)
Monthly income	0.416	-0.097	0.211	0.118	0.070	-0.181
]3000-4000]	(0.319)	(0.204)	(0.164)	(0.164)	(0.191)	(0.169)
Monthly income	0.239	-0.197	-0.010	0.132	0.218	-0.083
4000+	(0.310)	(0.237)	(0.163)	(0.158)	(0.167)	(0.129)
Bachelor’s degree	0.680	-0.035	-0.073	0.140	-0.002	0.359***
	(1.506)	(0.185)	(0.132)	(0.117)	(0.126)	(0.129)
Master’s degree	0.285	-0.139	0.147	0.184	-0.583***	0.572***
	(1.463)	(0.194)	(0.114)	(0.136)	(0.178)	(0.126)
Number of rooms in the	-0.097	-0.078	-0.027	0.018	-0.012	-0.037
home	(0.115)	(0.058)	(0.029)	(0.038)	(0.034)	(0.035)
Number of people at home during the lockdown	-0.132	-0.005	-0.074*	0.010	-0.014	-0.003
	(0.128)	(0.051)	(0.038)	(0.048)	(0.038)	(0.034)
Negative feelings	0.090	0.228***	0.037	0.166***	-0.071*	0.117***
	(0.084)	(0.056)	(0.032)	(0.037)	(0.040)	(0.032)
Future-biased	-0.067	0.032	-0.279*	0.046	0.002	0.145
	(0.283)	(0.190)	(0.144)	(0.131)	(0.155)	(0.113)

Present-biased	-0.411	0.075	-0.173	0.171	0.243	-0.083
	(0.335)	(0.156)	(0.120)	(0.124)	(0.160)	(0.136)
Constant	-1.261	-1.022***	-0.196	-1.456***	-1.245***	-0.545***
	(1.760)	(0.280)	(0.200)	(0.231)	(0.204)	(0.197)
Lambda (inverse mills	-56.561	138.128***	1.963	5.498	0.674*	0.024
ratio)	(78.047)	(50.227)	(5.448)	(7.768)	(0.395)	(0.290)
Observations	951	951	951	951	951	951

Notes: Bootstrap standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

A3. Full results of regressions presented in Table 2

Table A3.1. Full Regression Results for Tobacco

	Full sample	Full sample	Present-biased	Present-biased	Time-consistent	Time-consistent	Future-biased	Future-biased
Use in t0	0.262*	0.250	0.255	0.158	0.217	0.255	0.493*	0.673**
	(0.146)	(0.178)	(0.204)	(0.269)	(0.189)	(0.238)	(0.293)	(0.325)
Use in t1	0.522***	0.505***	1.177***	1.186***	0.344*	0.334	0.134	-0.388
	(0.148)	(0.166)	(0.164)	(0.235)	(0.185)	(0.226)	(0.222)	(0.279)
Use in t0 x use in t1	-0.015	-0.008	-0.608***	-0.567**	0.224*	0.216	0.022	0.318
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Decreased use during lockdown	-0.056	-0.042	-0.005	0.077	-0.066	-0.077	-0.087	-0.118
	(29.010)	(38.747)	(60.730)	(113.893)	(31.838)	(44.256)	(94.015)	(158.802)
Increased use during lockdown	-0.054	-0.057	-0.199**	-0.172	-0.001	-0.025	0.012	0.271
	(28.375)	(32.493)	(49.554)	(80.346)	(34.691)	(42.511)	(70.893)	(98.672)
Female		0.044		0.025		0.141**		-0.085
		(22.129)		(45.605)		(30.872)		(65.019)
Age]35-50]		-0.059		0.001		-0.057		-0.343
		(31.766)		(52.529)		(42.888)		(115.107)
Age]50-65]		0.019		0.065		-0.009		-0.154
		(34.597)		(59.832)		(43.055)		(108.172)
Age 65+		0.006		-0.075		0.039		-0.224
		(58.002)		(112.907)		(83.579)		(178.347)
Professional status: working		-0.003		0.056		-0.020		-0.299*
		(33.709)		(69.098)		(47.395)		(72.836)
Professional status: retired		-0.073		0.144		-0.137		-0.221
		(58.826)		(132.106)		(86.866)		(99.452)
Monthly income]2000-3000]		-0.007		0.097		0.038		-0.180
		(31.676)		(76.262)		(50.708)		(98.011)
Monthly income]3000-4000]		-0.062		-0.019		0.033		-0.181
		(31.805)		(58.101)		(43.567)		(104.277)
Monthly income 4000+		-0.046		-0.027		0.059		-0.208
		(30.636)		(62.726)		(35.338)		(110.458)
Bachelor's degree		0.051		0.052		0.038		-0.040
		(25.989)		(50.628)		(41.076)		(125.239)
Master's degree		-0.041		-0.123		-0.020		-0.133
		(30.994)		(85.681)		(46.893)		(77.630)
Number of rooms in the home		0.048		0.034		0.060		0.233
		(7.578)		(13.364)		(8.928)		(39.696)
Number of people at home during the lockdown		0.046		-0.031		0.067		0.015
		(10.568)		(22.147)		(15.091)		(27.051)
Negative feelings		0.010		-0.023		0.067		-0.061
		(8.906)		(21.560)		(12.565)		(19.914)
Observations	246	228	60	59	132	118	54	51
R-squared	0.554	0.564	0.714	0.769	0.579	0.618	0.426	0.567

Notes: Standardized coefficients based on regressions where consumption of tobacco in t2 is the dependent variable. Robust standard errors in parentheses. Significance levels: ***p<0.01, **p<0.05, *p<0.1.

Table A3.2. Full Regression Results for Alcohol

	Full sample	Full sample	Present-biased	Present-biased	Time-consistent	Time-consistent	Future-biased	Future-biased
Use in t0	0.709***	0.728***	0.662***	0.608***	0.865***	1.023***	1.190***	1.189***
	(0.136)	(0.136)	(0.101)	(0.094)	(0.250)	(0.238)	(0.148)	(0.142)
Use in t1	0.684***	0.629***	0.145*	0.170**	0.593**	0.453*	-0.005	-0.063
	(0.146)	(0.142)	(0.076)	(0.070)	(0.214)	(0.207)	(0.186)	(0.186)
Use in t0 x use in t1	-0.619***	-0.594***	0.201	0.218	-0.749***	-0.780***	-0.318	-0.262
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Decreased use during lockdown	-0.008	0.012	-0.054***	-0.043**	-0.003	0.017	-0.060**	-0.035
	(1.629)	(1.709)	(1.517)	(1.420)	(2.509)	(2.613)	(2.305)	(2.412)
Increased use during lockdown	-0.062**	-0.040	-0.044*	-0.048**	-0.042	-0.006	0.007	0.043
	(2.363)	(2.341)	(1.847)	(1.634)	(3.585)	(3.612)	(1.978)	(2.749)
Female		-0.062***		-0.029*		-0.059**		-0.027
		(1.336)		(1.100)		(1.763)		(1.461)
Age]35-50]		-0.007		-0.013		-0.005		-0.002
		(1.653)		(1.495)		(2.818)		(2.287)
Age]50-65]		0.019		-0.012		0.014		0.018
		(1.607)		(1.921)		(2.416)		(2.490)
Age 65+		0.027		0.001		0.033		-0.009
		(1.596)		(2.339)		(2.439)		(3.748)
Professional status: working		0.056*		-0.018		0.074		0.025
		(1.912)		(1.907)		(2.951)		(2.176)
Professional status: retired		0.077**		0.010		0.093*		0.090**
		(2.406)		(2.187)		(3.724)		(2.221)
Monthly income]2000-3000]		0.020		0.018		0.014		-0.032
		(1.571)		(1.703)		(2.574)		(2.176)
Monthly income]3000-4000]		-0.003		0.005		-0.009		-0.079**
		(1.844)		(1.584)		(3.157)		(2.664)
Monthly income 4000+		-0.006		0.036		-0.018		-0.028
		(2.135)		(1.765)		(3.211)		(3.024)
Bachelor's degree		0.041*		0.036*		0.056*		-0.002
		(1.423)		(1.336)		(2.185)		(1.458)
Master's degree		0.044*		0.020		0.043		0.008
		(1.679)		(1.302)		(2.453)		(2.249)
Number of rooms in the home		0.028		0.027		0.012		0.014
		(0.356)		(0.376)		(0.528)		(0.612)
Number of people at home during the lockdown		-0.015		-0.004		-0.015		-0.012
		(0.615)		(0.624)		(0.892)		(0.568)
Negative feelings		0.033**		-0.006		0.037		-0.019
		(0.344)		(0.340)		(0.605)		(0.638)
Observations	782	722	178	171	459	418	145	133
R-squared	0.767	0.785	0.946	0.950	0.713	0.740	0.921	0.934

Notes: Standardized coefficients based on regressions where consumption of alcohol in t2 is the dependent variable. Robust standard errors in parentheses. Significance levels: ***p<0.01, **p<0.05, *p<0.1.

Table A3.3. Full Regression Results for Screens

	Full	Full	Present-	Present-	Time-	Time-	Future-	Future-

	sample	sample	biased	biased	consistent	consistent	biased	biased
Use in t0	0.602***	0.632***	0.809***	0.972***	0.401***	0.397***	0.670***	0.788***
	(0.081)	(0.089)	(0.163)	(0.153)	(0.108)	(0.110)	(0.172)	(0.163)
Use in t1	0.614***	0.559***	0.503**	0.382**	0.546***	0.501***	0.623***	0.473***
	(0.070)	(0.076)	(0.140)	(0.123)	(0.091)	(0.096)	(0.152)	(0.119)
Use in t0 x use in t1	-0.454***	-0.451***	-0.589**	-0.662**	-0.069	-0.013	-0.735***	-0.752***
	(0.009)	(0.009)	(0.014)	(0.015)	(0.013)	(0.012)	(0.005)	(0.004)
Decreased use during lockdown	-0.025	-0.038	-0.092	-0.135**	0.032	0.011	-0.046	-0.064
	(0.199)	(0.210)	(0.352)	(0.323)	(0.286)	(0.303)	(0.406)	(0.454)
Increased use during lockdown	-0.045	-0.030	0.038	0.065	-0.090**	-0.096**	0.012	0.101
	(0.169)	(0.197)	(0.347)	(0.352)	(0.193)	(0.212)	(0.508)	(0.550)
Female		-0.018		0.006		-0.010		-0.014
		(0.095)		(0.158)		(0.107)		(0.216)
Age]35-50]		-0.039		0.002		-0.027		-0.117
		(0.154)		(0.287)		(0.202)		(0.405)
Age]50-65]		-0.007		0.077		-0.045		-0.029
		(0.153)		(0.298)		(0.195)		(0.381)
Age 65+		-0.039		0.054		-0.073		0.019
		(0.225)		(0.404)		(0.277)		(0.645)
Professional status: working		0.017		0.043		0.035		-0.113
		(0.168)		(0.287)		(0.210)		(0.421)
Professional status: retired		0.066		0.092		0.074		-0.093
		(0.251)		(0.412)		(0.288)		(0.475)
Monthly income]2000-3000]		-0.013		-0.063		-0.006		-0.007
		(0.162)		(0.251)		(0.189)		(0.411)
Monthly income]3000-4000]		-0.053*		-0.102*		-0.024		-0.068
		(0.154)		(0.263)		(0.172)		(0.412)
Monthly income 4000+		-0.040		-0.100*		0.003		-0.035
		(0.166)		(0.229)		(0.174)		(0.471)
Bachelor’s degree		0.031		0.126**		-0.029		0.051
		(0.106)		(0.211)		(0.133)		(0.245)
Master’s degree		0.030		0.106*		-0.007		0.015
		(0.116)		(0.214)		(0.139)		(0.315)
Number of rooms in the home		0.033		-0.040		0.043		0.060
		(0.031)		(0.050)		(0.037)		(0.093)
Number of people at home during the lockdown		-0.031		0.012		-0.067**		0.028
		(0.036)		(0.071)		(0.040)		(0.119)
Negative feelings		0.014		-0.005		-0.004		0.021
		(0.034)		(0.055)		(0.041)		(0.071)
Observations	1,038	951	244	231	576	523	218	197
R-squared	0.583	0.582	0.572	0.590	0.655	0.674	0.509	0.523

Notes: Standardized coefficients based on regressions where use of screen in t2 is the dependent variable. Robust standard errors in parentheses. Significance levels: ***p<0.01, **p<0.05, *p<0.1.

A4. Full results of regressions presented in Table 3

Table A4. Full Regression Results of the Hysteresis Test Using the Intensity of Time Inconsistency $(X2 - X1)$~~X2-X1)~~

	Tobacco		Alcohol		Screens	
Use in t0	0.276**	0.289*	0.702***	0.718***	0.602***	0.640***
	(0.138)	(0.168)	(0.137)	(0.138)	(0.081)	(0.091)
Use in t1	0.497***	0.456***	0.684***	0.627***	0.614***	0.555***
	(0.137)	(0.154)	(0.147)	(0.144)	(0.070)	(0.076)
Intensity of time inconsistency	-0.128**	-0.141***	-0.027	-0.037	0.011	0.036
x use in t1	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Use in t0 x use in t1	0.008	0.004	-0.611***	-0.580***	-0.454***	-0.457***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.009)	(0.009)
Decreased use during	-0.057	-0.043	-0.007	0.013	-0.024	-0.037
lockdown	(28.087)	(37.183)	(1.635)	(1.712)	(0.199)	(0.209)
Increased use during lockdown	-0.044	-0.045	-0.063**	-0.044	-0.045	-0.028
	(27.533)	(31.586)	(2.362)	(2.331)	(0.169)	(0.201)
Female		0.044		-0.063***		-0.016
		(22.012)		(1.339)		(0.093)
Age]35-50]		-0.054		-0.006		-0.039
		(32.009)		(1.635)		(0.154)
Age]50-65]		0.021		0.016		-0.007
		(34.884)		(1.605)		(0.153)
Age 65+		0.026		0.026		-0.042
		(55.485)		(1.587)		(0.222)
Professional status: working		0.010		0.058*		0.014
		(34.140)		(1.911)		(0.168)
Professional status: retired		-0.093		0.081**		0.068
		(55.636)		(2.408)		(0.249)
Monthly income]2000-3000]		-0.013		0.020		-0.016
		(31.073)		(1.581)		(0.164)
Monthly income]3000-4000]		-0.085		-0.003		-0.054*
		(32.433)		(1.844)		(0.155)
Monthly income 4000+		-0.060		-0.005		-0.042
		(29.499)		(2.138)		(0.168)
Bachelor’s degree		0.028		0.043**		0.032
		(25.410)		(1.411)		(0.105)
Master’s degree		-0.042		0.046*		0.031
		(30.269)		(1.663)		(0.116)
Number of rooms in the home		0.054		0.028		0.035
		(7.493)		(0.355)		(0.031)
Number of people at home		0.042		-0.017		-0.030
during the lockdown		(10.640)		(0.608)		(0.036)
Negative feelings		0.017		0.032**		0.013
		(8.954)		(0.345)		(0.034)
Observations	246	228	782	722	1,038	951
R-squared	0.570	0.582	0.768	0.786	0.583	0.584

Notes: Standardized coefficients based on regressions where consumption of addictive products (tobacco, alcohol or screens) in t2 is the dependent variable. Robust standard errors are presented in parentheses. Significance levels are denoted as ***p<0.01, **p<0.05, *p<0.1.

A5. Sensitivity analysis: removal of the highest consumption values for alcohol and screen use

Table A5. Regression Results after Removing Observations with Weekly Alcohol Consumption ≥75 and Daily Screen Use ≥18

	Alcohol		Screens	
	Without controls	With controls	Without controls	With controls
Use in t1	0.327**	0.240**	0.524***	0.481***
	(0.135)	(0.104)	(0.074)	(0.080)
Intensity of time	-0.018	-0.030	0.036	0.043
inconsistency x use in t1	(0.002)	(0.002)	(0.002)	(0.002)
#Obs	777	717	1,036	950
R-squared	0.820	0.839	0.589	0.594

Notes: Standardized coefficients based on regressions where consumption of addictive products (alcohol or screens) in t2 is the dependent variable. The controls are the same as in Table 3. Robust standard errors are presented in parentheses. Significance levels are denoted as ***p<0.01, **p<0.05, *p<0.1.

A6. Sensitivity analysis: reclassification of extremely impatient respondents as present-biased

Table A6.1. Regression Results After Recoding as Present-Biased All Respondents Who Scored 0 on a 0–10 Patience Scale (i.e. 18 changes)

	Subsample of present-biased individuals		Subsample of time-consistent individuals		Subsample of future-biased individuals	
	Without controls	With controls	Without controls	With controls	Without controls	With controls
Tobacco	1.123***	1.179***	0.334	0.324	0.171	-0.257
	(0.165)	(0.231)	(0.187)	(0.229)	(0.217)	(0.286)
#Obs	65	64	128	114	53	50
R-squared	0.665	0.739	0.579	0.620	0.458	0.583
Alcohol	0.168**	0.195***	0.588**	0.449	-0.003	-0.067
	(0.076)	(0.067)	(0.214)	(0.208)	(0.186)	(0.186)
#Obs	189	180	452	412	141	130
R-squared	0.937	0.944	0.712	0.738	0.921	0.934
Screens	0.652**	0.650**	0.514***	0.463***	0.654***	0.478***
	(0.162)	(0.189)	(0.091)	(0.096)	(0.154)	(0.119)
#Obs	262	246	565	513	211	192
R-squared	0.578	0.590	0.650	0.670	0.510	0.522

Notes: Standardized coefficients based on regressions where consumption of addictive products (tobacco, alcohol or screens) in t2 is the dependent variable. The controls are the same as in Table 2. Robust standard errors are presented in parentheses. Significance levels are denoted as ***p<0.01, **p<0.05, *p<0.1.

Table A6.2. Regression Results After Recoding as Present-Biased All Respondents Who Scored 0 or 1 on a 0–10 Patience Scale (i.e. 32 changes)

	Subsample of present-biased individuals		Subsample of time-consistent individuals		Subsample of future-biased individuals	
	Without controls	With controls	Without controls	With controls	Without controls	With controls
Tobacco	0.974***	1.119***	0.399*	0.467*	0.171	-0.257
	(0.178)	(0.285)	(0.185)	(0.226)	(0.217)	(0.286)
#Obs	72	71	121	107	53	50
R-squared	0.538	0.631	0.644	0.678	0.458	0.583
Alcohol	0.161*	0.183**	0.597**	0.454	-0.003	-0.067
	(0.075)	(0.069)	(0.223)	(0.217)	(0.186)	(0.186)
#Obs	198	187	443	405	141	130
R-squared	0.936	0.942	0.711	0.737	0.921	0.934
Screens	0.630***	0.613**	0.520***	0.472***	0.654***	0.478***
	(0.154)	(0.182)	(0.092)	(0.098)	(0.154)	(0.119)
#Obs	276	258	551	501	211	192
R-squared	0.588	0.604	0.645	0.665	0.510	0.522

Notes: Standardized coefficients based on regressions where consumption of addictive products (tobacco, alcohol or screens) in t2 is the dependent variable. The controls are the same as in Table 2. Robust standard errors are presented in parentheses. Significance levels are denoted as ***p<0.01, **p<0.05, *p<0.1.