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Impulsive youth, cautious age? Time consistency and addiction over the life cycle

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Abstract

Age-based restrictions on addictive goods are partly motivated by the view that young people have time-inconsistent preferences. We test this hypothesis using longitudinal data on individual cigarette consumption from the Russia Longitudinal Monitoring Survey for 1994–2020. We estimate a rational-addiction model with quasi-hyperbolic discounting separately for young and adult smokers. We find no evidence of present bias in either group: the estimates are close to the time-consistent benchmark for both. However, the estimated long-run discount factor is substantially lower for young smokers (0.54) than for adults (0.97), indicating much greater impatience early in the life cycle. The age gradient persists across selected alternative age windows, pointing to substantial life-cycle heterogeneity in patience that would be obscured by models imposing a common long-run discount factor across ages.

Keywords: rational addiction, smoking behavior, young and adult smokers, present bias, time preferences
JEL Codes: D15, I12, J13

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1 Introduction

In the analysis of intertemporal consumption, the assumption of exponential discounting has been questioned since the mid-twentieth century (Strotz 1956). To address these critiques while preserving analytical parsimony, the quasi-hyperbolic discounting framework was developed. This model is characterized by present-biased preferences, whereby all future utilities are further discounted by a constant parameter β (see, for instance, Pollak 1968; Laibson 1997). Such a formulation permits time-inconsistent behavior: a consumption plan deemed optimal today may not be implemented in the future, because once the future becomes the present, present-biased preferences reassert themselves and previously chosen actions are no longer optimal. This outcome arises for naive consumers, who fail to anticipate that their future selves will exhibit the same bias.[1] The analysis of time-inconsistent preferences remains an active area of research (see Grossman 2022), particularly because, until recently, empirical tests of quasi-hyperbolic discounting were largely confined to experimental settings.[2]

The assumption of time-consistent agents is particularly consequential in the analysis of addictive consumption, a context in which the Rational Addiction model (Becker and Murphy 1988; Becker et al. 1994) has been extensively debated. Quasi-hyperbolic discounting was first incorporated into the Rational Addiction framework by Gruber and Köszegi (2001), who showed that dynamic inconsistency can yield markedly different policy implications. Despite the relevance of this extension, empirical tests of time inconsistency in addictive consumption remained absent for many years, largely because its empirical specification was thought to be observationally indistinguishable from the general formulation of the Rational Addiction model.[3] This identification issue was addressed by Piccoli

[1] Sophisticated consumers, who correctly foresee their future present bias, instead solve a different optimization problem, often modeled as a sequential game played against future selves.

[2] See Blow et al. (2021) and Freeman and Laughren (2024) for recent empirical contributions.

[3] The general specification of the Rational Addiction model, which is rarely estimated in the empirical

and Tiezzi (2021), who demonstrate that the general specification of the quasi-hyperbolic Rational Addiction model permits a direct test of whether the present-bias parameter β differs from unity and allows the identification of its upper bound.

The empirical literature on forward-looking addictive consumption has largely relied on the rational-addiction framework, although alternative approaches have also been proposed. Aristei and Pieroni (2010), for example, use a dynamic adjustment-cost model with rational expectations and find intertemporal dependence consistent with forward-looking alcohol and tobacco consumption.

Building on Piccoli and Tiezzi (2021), we address a related question that has gained prominence following the adoption of State Tobacco 21 laws in the United States, which raised the minimum legal age for purchasing tobacco products to 21 (Hansen et al. 2023). A key argument in the policy debate is that younger individuals are more likely to exhibit present-biased preferences (Crettez and Deloche 2021), and are therefore less able to fully account for the future health consequences of smoking, making them more susceptible to addiction. This concern is particularly salient if young people are viewed as naive present-biased consumers. Empirical evidence based on representative consumption data, however, remains scarce. This paper seeks to fill this gap by testing whether young smokers exhibit evidence of quasi-hyperbolic discounting and by comparing their time preferences with those of adults, using data from the Russia Longitudinal Monitoring Survey for the period 1994–2020.

The results provide no evidence of time inconsistency among adult Russian smokers and yield discount rates consistent with those commonly reported in the empirical literature. Young smokers likewise show no evidence of present-biased preferences, with an estimated upper bound for β of 0.99, identical to that obtained for adults. However, their estimated

literature, includes current, lead, and lagged prices of the good in the demand equation. This contrasts with the more commonly estimated simplified specification, which includes only current prices.

discount factor is substantially lower—0.54 compared with 0.97 for adults—implying a markedly stronger discounting of future utility. These findings point to marked age-related heterogeneity in long-run discounting: young smokers are substantially more impatient than adults, despite no evidence of present bias.

The remainder of the paper is structured as follows. Section 2 presents a short theoretical description of the model used in the empirical analysis. Section 3 describes the data, sample selection and empirical specification of the model. Section 4 presents the results and Section 5 concludes.

2 Model

The model specification is as follows. Individuals are assumed to maximize the sum of lifetime discounted utility

$$\max\ U_t + \beta \sum_{i=1}^{\infty} \delta^i U_{t+i} = U_t + \beta\delta U_{t+1} + \beta\delta^2 U_{t+2} + ... \tag{1}$$

where $\delta = \frac{1}{(1+r)}$ is the long-run discount factor, r is the discount rate (that coincides with the interest rate in the budget constraints), and the extra discount parameter $\beta \in (0, 1]$ is intended to capture the essence of hyperbolic discounting, namely, that the discount factor between consecutive future periods (δ) is larger than that between the current period and the next period ($\beta\delta$). If $\beta \neq 1$, time preferences in equation (1) are dynamically inconsistent, in the sense that the optimal consumption plan established in t is inconsistent with the one that will be established in $t+1$. As shown by O'Donoghue and Rabin (2002), the equilibrium of both naïve and time-consistent individuals solves the same optimization problem. Therefore, the demand equation that solves (1) applies to both time-consistent and naïve consumers. As in the general specification of the rational addiction model, the interaction between past and future consumption is modeled by the investment function $A_t = (1-\gamma)A_{t-1} + C_{t-1}$, with A_t being interpreted as an "addiction stock" that depreciates

over time at rate $\gamma < 1$ and increases with current consumption. The consumer solves the maximization problem such that $C_0 = C^0$ and $(Y_t + P_t C_t) + \sum_{i=1}^{\infty} \delta^i (Y_{t+i} + P_{t+i} C_{t+i}) = W_0$, where C^0 measures the previous level of consumption.

Taking a quadratic utility function in the three arguments and solving the consumer problem produces the following Euler equation:[4]

$$C_t = \theta_0 + \theta_L C_{t-1} + \theta_F \delta C_{t+1} - \theta_1 \left[1 + (1-\gamma)^2 \delta\right] P_t + \theta_1 (1-\gamma) P_{t-1} + \theta_1 \delta (1-\gamma) P_{t+1} \quad (2)$$

where:

$$\begin{aligned}
\Omega &= \alpha_{CA}(1+\beta)\delta(1-\gamma) - \alpha_{AA}\beta\delta - \alpha_{CC}\left[1 + \delta(1-\gamma)^2\right] > 0 \\
\theta_0 &= \frac{\gamma}{\Omega}\left[\kappa + \alpha_C\big(\delta(1-\gamma) - 1\big) - \alpha_A \beta \delta\right] \\
\theta_L &= \frac{1}{\Omega}\left[\alpha_{CA} - \alpha_{CC}(1-\gamma)\right] > 0 \qquad (3) \\
\theta_F &= \frac{1}{\Omega}\left[\beta\alpha_{CA} - \alpha_{CC}(1-\gamma)\right] > 0 \qquad (4) \\
\theta_1 &= \frac{\lambda}{\Omega} > 0
\end{aligned}$$

The rational addiction model with quasi-hyperbolic discounting encompasses the original formulation of the rational addiction model. In particular, setting $\beta = 1$, the model reduces to the standard Becker, Grossman, Murphy (1994) (BGM, henceforth) rational addiction model, which implies time-consistency. Equation (2) can thus be used to test whether consumers are time-consistent or not by testing the equality $\theta_L = \theta_F$, as the only difference between the two coefficients is the presence of β in θ_F.

After some manipulation, equation (2) can be written as

$$C_{it} = \phi_0 + \phi_L C_{it-1} + \phi_F C_{it+1} + \varphi_T P_{it} + \varphi_L P_{it-1} + \varphi_F P_{it+1}, \quad (5)$$

which, if no parameter restrictions are imposed, allows us to identify all needed structural parameters to perform the standard battery of tests for rational addiction and to test for

[4]For a detailed derivation of the Euler equation, see Piccoli and Tiezzi (2021).

time-consistency. The time consistency test tests the null[5]

$$\phi_L \varphi_F - \phi_F \varphi_L = 0 \ . \tag{6}$$

If the test rejects the null hypothesis, then $\beta \neq 1$ and the data do not support time-consistent preferences in favor of quasi-hyperbolic discounting for naïve consumers.

Given the parametric specification of equation (2) and the corresponding reduced-form equation (5), it is not possible to directly point-identify the value of the present bias parameter β. Nevertheless, it is possible to find an upper bound for β compatible with the estimated coefficients. The upper bound for the present-bias parameter is $\beta_{max} = \frac{\phi_F \varphi_L}{\phi_L \varphi_F}$ (for a proof see Piccoli and Tiezzi 2021).[6]

3 Empirical strategy

We estimate separate empirical demand equations for young and adult individuals, of the form:

$$C_{it} = \phi_0 + \phi_L C_{it-1} + \phi_F C_{it+1} + \varphi_T P_{it} + \varphi_L P_{it-1} + \varphi_F P_{it+1} + \eta_X X_{it} + v_i + d_t + u_{it} \tag{7}$$

where C_{it} is the number of smoked cigarettes by individual i in period t, P_{it} is the real price of cigarettes, X_{it} is a vector of exogenous economic and socio-demographic variables that affect cigarette consumption, v_i are individual fixed effects capturing time-invariant preferences that are correlated with lead and lagged consumption and probably with other determinants of consumption, d_t are time fixed effects, and $u_{it} = \xi_1 e_t + \xi_2 e_{t+1}$ is the idiosyncratic error term.

[5]Quick proof: since $\delta = \frac{\varphi_F}{\varphi_L}$, $\theta^L = \phi_L$, and $\theta^F = \frac{\phi_F}{\delta} = \frac{\phi_F \varphi_L}{\varphi_F}$, from equations (3) and (4) it is possible to note that $\beta = 1$ if and only if $\theta_L = \theta_F$, i.e., $\phi_L \varphi_F = \phi_F \varphi_L$, or $\phi_L \varphi_F - \phi_F \varphi_L = 0$

[6]Extensive simulations of the structural model for a wide range of plausible values of the parameters suggest that the true value of the β parameter tends to be very close to its upper bound β_{max}.

There are two problems that will bias OLS estimates of equation (7). First, OLS estimates can suffer from an omitted variable bias due to unaccounted demand shifters that may also be serially correlated (Becker et al. 1994). Second, there is measurement error when we use actual values of C_{it+1}. C_{it+1} in equation 7 should be interpreted as planned cigarette consumption at time $t+1$ using the information at time t. However, planned and actual consumption at time $t+1$ might differ. Since we use actual cigarette consumption at time $t+1$ to proxy planned consumption, C_{it+1} might be affected by measurement error which will enter the idiosyncratic error term (Picone 2005).

The standard route to correct for the endogeneity bias is to follow Arellano and Bond (1991) in using a GMM procedure to obtain the vector of parameters. They propose to take first-differences to deal with the unobserved fixed effects and then use the suitably lagged levels of the endogenous and predetermined variables as instruments for the first-differenced series, under the assumption that the error term in levels is spherical and taking into account the serial correlation induced by the first-difference transformation. This idea extends to the case of lags and leads of the dependent variable and to the case where serial correlation already exists in the error term of the original model, as in equation (7).

The first-differenced GMM estimator is known to be poorly behaved in terms of finite sample properties (bias and imprecision) when instruments are weak. Better finite sample properties can be obtained with system-GMM (Arellano and Bover 1995; Blundell and Bond 1998). This estimator exploits additional moment conditions, which are valid under the constant correlated effects assumption (Bun and Sarafidis 2015). The complete list of available moment conditions is detailed in section A.1 of the Appendix. As to the choice of the transformation used to remove individual effects in GMM estimators, while first differencing (FD) is one option, Arellano and Bover (1995) propose forward orthogonal deviations (FOD) as an alternative transformation for models with predetermined instruments, involving subtracting the mean of all future observations for each individual.

The FOD transformation does not introduce a moving average process in the disturbance, i.e. orthogonality among errors is maintained, and preserves the sample size in panels with gaps, as in our case, where FD would reduce the number of observations (Roodman 2009b). Valid moment conditions for the FOD model in presence of endogenous regressors (Kripfganz 2019) are: $E(C_{it-s}\Delta u_{it}) = 0$ for $t = 4, ..., T-1$ and $s \geq 2$. This allows the use of lagged levels of the observed consumption series dated $t-2$ and earlier as instruments for the FOD equation.

3.1 Data

To the best of our knowledge, the longest longitudinal survey that collects individual information on the number of cigarettes smoked along with local-level prices and that follows individuals for as long as possible is the Russia Longitudinal Monitoring Survey (RLMS-HSE), which started in 1994 and is still ongoing. The survey is conducted by the Higher School of Economics and ZAO Demoscop, together with the Carolina Population Center, and follows individuals and their families from childhood to adulthood.[7] Households participating in the survey were selected through a multistage probability sampling procedure to guarantee cross-sectional national representativeness. The survey covers approximately 5,000 households, 12,000 adults and 2,000 children (aged up to 15 years) per wave.

The empirical analysis of cigarette addiction is thus based on waves 5 to 29 (corresponding to years 1994 to 2020) of the RLMS-HSE. For each individual aged 13 years and above, the survey asks whether they smoke and, if so, the number of cigarettes smoked per day. This is the main consumption measure used in our study. The price variable is computed from the community questionnaire, where interviewers go to local stores in the community and check minimum and maximum prices of a large sample of commodities, including domestic- and foreign-branded cigarettes. Because several missing values are recorded at

[7]More information can be found in the RLMS-HSE site: http://www.cpc.unc.edu/projects/rlms-hse.

the community level (if, for instance, no store had a particular item or if the store was closed), the price was averaged across communities within the same primary sample units to reduce the impact of measurement errors. Because the prices are at the current level, and the survey does not provide consumer price indices to deflate prices, we compute a consumer price index at the PSU level following the Törnqvist procedure (Törnqvist 1936). The reference price is that of the Moscow PSU in 1998, and the index is computed on a wide set of food commodities, excluding tobacco and alcohol items. Cigarette prices–together with the other monetary variables described below–are then deflated using this consumer price index.

To observe young smokers who still live with their parents, but avoid complex multi-family households, we selected smokers living in households with no more than four members. The equation for the young-smoker sample is estimated for individuals no older than 21, for which about two thousand observations and about one thousand individuals are available. The adults' equation is estimated for individuals aged 30 to 65, corresponding to about 31 thousand observations and 6.4 thousand individuals, while alternative age ranges are considered for a robustness analysis. We use identical specifications for both equations with a minimal set of strictly exogenous covariates, X_{it}, which includes: wave indicators, gender of the respondent ($female = 1$), age (in years) of the respondent and its square. Time dummies have been specified in the level model only to avoid redundancy (Kripfganz 2019).[8] Descriptive statistics for the two samples are reported in Table 1.

4 Results

Table 2 reports estimates of model (7) for young and adult individuals. The table also reports the instrument count and the p-value of the Hansen test for the joint validity of

[8]We estimated the models using xtabond2 in Stata 18.

Table 1: Descriptive statistics: Young & adults

Variables	Young ($age \leq 21$)		Adults ($30 \leq age \leq 65$)	
	Mean	Std. Dev.	Mean	Std. Dev.
C_t	11.629	6.132	16.530	7.947
P_t	30.204	29.964	46.160	40.079
Gender	0.250	0.433	0.254	0.435
Age	18.905	1.782	44.905	9.770
# Obs	2,037		31,189	

all instruments (Hansen p-value), together with the Arellano-Bond test for second- and third-order serial correlation in the residuals.[9]

Estimates are consistent with the rational addiction framework for both young and adult individuals. In both equations past consumption has a significant positive effect. Future consumption also has a significant positive effect, supporting the idea that smokers' behavior is forward looking. The coefficient of lagged price is greater than the coefficient of lead price, determining a positive discount rate. We obtain a negative coefficient on the current price and a positive coefficient on both past and future prices. So, the signs on the two consumption variables and on the three price variables conform to theoretical predictions. The p-values of the Hansen J statistic for over-identifying restrictions for the full model are consistent with the null hypothesis of validity of the overidentifying restrictions. Finally, the Arellano-Bond test for third-order autocorrelation in the residuals does not detect third-order serial correlation in the residuals of either of the two equations.

As to the covariates, being female has a negative and statistically significant impact on the number of cigarettes smoked. Age and smoked cigarettes display a nonlinear relationship in both equations: one additional year of age is associated with an increase in the

[9]Because in our model current consumption depends on both past and future consumption, this is an autoregressive process of order 2 (AR2) and we have second-order serial correlation by construction. So, for the validity of our instrument set, we need to detect no serial correlation of order 3 in the residuals.

Table 2: General rational addiction model estimates: Young & adults

Variables	Young ($age \leq 21$)	Adults ($30 \leq age \leq 65$)
C_{t-1}	0.339***	0.442***
	(0.079)	(0.076)
C_{t+1}	0.183***	0.427***
	(0.071)	(0.088)
P_t	-0.060**	-0.033***
	(0.029)	(0.013)
P_{t-1}	0.046*	0.017**
	(0.026)	(0.007)
P_{t+1}	0.025**	0.016*
	(0.010)	(0.009)
Gender	-1.220**	-0.780**
	(0.472)	(0.314)
Age	0.683**	0.059**
	(0.311)	(0.027)
Age^2	-0.012**	-0.001**
	(0.006)	(0.000)
Time dummies	Yes	Yes
Hansen p-value full	0.100	0.537
p-value Arellano-Bond test for AR(2)	0.001	0.000
p-value Arellano-Bond test for AR(3)	0.146	0.358
# Obs	2,037	31,189
Instruments count	172	136

Notes: Robust SE in parentheses using Windmeijer correction. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

number of cigarettes smoked per day but at a decreasing rate. This non-linear relationship is stronger for young smokers for whom we obtain larger coefficients (in absolute value) for both Age and Age squared, signaling that, compared to adult individuals, one additional year of age is associated with a larger increase in the number of cigarettes smoked per day and with a larger decrease in marginal consumption.

An important scale-free measure of price responsiveness, more directly comparable across groups and informative for policy discussions, is the price elasticity of demand. Short- and long-run elasticities computed from the general specification are imprecisely estimated due to strong collinearity among current, lagged, and lead prices. We therefore compute elasticities for both young and adult individuals using the restricted specification, which yields more stable and interpretable estimates. These elasticities are reported in Table A1 in the Appendix.

The results show that the long-run price response exceeds the short-run response for both groups, consistent with the presence of addiction. Moreover, the long-run elasticity is substantially larger in absolute value for adults than for younger individuals. This suggests that price-based policies may be more effective in reducing consumption among groups with lower discount rates. This pattern is consistent with a rational addiction framework in which more patient individuals place greater weight on future consequences when making current consumption decisions.

Table 3 shows the results of the time consistency tests and time-preference parameters computed from the estimated parameters. The test consists of testing the null hypothesis $\phi_1\phi_5 - \phi_2\phi_4 = 0$. For the non-linear test, under the null, the test statistic has a χ^2 distribution with 1 degree of freedom. We obtain a test statistics of $\chi^2(1) = 0.00$ with a $Prob > \chi^2 = 0.993$ for young individuals, and a test statistics of $\chi^2(1) = 0.00$ with a $Prob > \chi^2 = 0.997$ for adult individuals. We therefore do not reject the restrictions implied by time-consistent preferences in either sample. The estimated upper bound for

Table 3: Time consistency tests

	Young (age $\leq$ 21)	Adults (30 $\leq$ age $\leq$ 65)
β_{max}	0.992	0.997
Time-consistency nl-test $\chi^2(1)$ (p-val)	0.00 (0.993)	0.00 (0.997)
Discount factor	0.543	0.969
Discount rate	0.842	0.032

the present bias parameter is $\beta_{max} = \frac{\widehat{\theta}^{+}}{\widehat{\theta}^{-}} = \frac{\phi_2\phi_4}{\phi_1\phi_5} = 0.992$ for young individuals and 0.997 for adult individuals, which are only marginally smaller than 1. Thus, we cannot reject the null hypothesis $\beta_{max} = 1$ for either sample.

As to the estimated discount factor and discount rate, for adults we estimate a discount factor of $\delta = \phi_5/\phi_4 = 0.969$ and a discount rate of 0.032, while for young smokers we estimate a discount factor $\delta = \phi_5/\phi_4 = 0.543$ and a discount rate of 0.842.

To assess whether the large young–adult gap in discounting reflects a genuine behavioral pattern rather than an econometric artifact, we re-estimate the model across a sequence of alternative age windows that progressively shifts the estimation window toward younger ages. The age ranges reported in Table 4 are not arbitrary: we retain only windows that satisfy a common set of quality criteria. Specifically, each specification (i) lowers the age threshold relative to the adult benchmark, (ii) can be estimated using the same model specification and instrument set adopted for the adult equation, (iii) yields price coefficients that are individually significant at least at the 10% level (and in most cases at the 5% level), and (iv) passes the diagnostic and specification tests discussed earlier.

Applying these restrictions improves comparability across samples and reduces the risk that the results are driven by weak identification or specification instability in particular subsamples. The exercise is nevertheless informative rather than exhaustive: it considers

only age windows that can be estimated using the common specification and instrument set and does not examine every possible age cutoff. Conditional on this common empirical design, the estimated discount factor declines monotonically as younger individuals are included and older individuals are excluded, while the estimated discount rate rises correspondingly. This pattern provides complementary evidence that the baseline young–adult gap is not specific to the two benchmark age windows.

Specifically, the first row reports the results for the adult population as previously defined. Already in the second row, where the age window is shifted downward by 5 years, the discount factor declines from 0.97 to 0.95, implying an increase in the discount rate of 2.5 percentage points, from 3.2% to 5.7%. The $\beta_{\max}$ estimate is slightly lower, but still not statistically different from 1. Lowering the age window by a further 5 years raises the discount rate to 7.2%, while the test again does not reject time consistency. As the age range is shifted further toward younger cohorts, estimated discount rates keep increasing, especially when younger teenagers are included and the upper age limit is reduced. In the 12–41 age range, the estimated discount rate reaches 33%. Although this is still well below the 84% estimated for individuals aged up to 21, it suggests that progressively shifting the sample toward younger ages moves the estimate in that direction.[10] The time-consistency restrictions are not rejected for any of the age windows considered: the corresponding Wald-test p-values range from approximately 0.87 to 1.00.

In addition, to ensure that model specification is not driving the results, Appendix A.2 present the result of estimating the restricted version of the rational addiction model for young and adult smokers. The restricted model differs from the full specification in that it

[10] when using exactly the same model specification as for adults, attempts to lower the age range even further produce non-significant estimates for some price parameters, making the implied discount rates unreliable. At the same time, adopting different specifications or instrument sets would weaken this robustness exercise, as results would then depend on discretionary choices beyond the age range itself.

Table 4: Comparison of discounting and present bias for varying age windows

Age range	Discount factor	Discount rate	$\beta_{\max}$	p-val
$30 \leq$ age ≤ 65	0.969	0.032	0.997	0.997
$25 \leq$ age ≤ 60	0.946	0.057	0.960	0.944
$20 \leq$ age ≤ 55	0.933	0.072	1.049	0.944
$16 \leq$ age ≤ 51	0.924	0.082	1.133	0.868
age ≤ 46	0.861	0.162	1.006	0.994
age ≤ 41	0.752	0.330	1.086	0.886

Note: All estimations conducted with exactly the same specification as for adults, including the instrument set. Full estimation tables for each age window are available upon request.

excludes lead and lagged prices. The full specification is needed to identify the structural parameters that allows us to test for time-inconsistency. Because the time-consistency test does not reject $\beta = 1$ for any of the age groups considered, under the additional assumption that the addiction stock fully depreciates from one period to another and imposing $\beta = 1$, the restricted version can also be used to identify the structural discount factor δ by computing the ratio of the lead to lagged consumption coefficients. Results, presented in Table A1 are remarkably close to our main estimates, with the discount factor being 0.988 vs 0.969 for adults, and 0.538 vs 0.543 for the young.

Within the rational-addiction framework, δ is a structural parameter governing intertemporal choices. Our estimates therefore recover the value of δ that rationalizes observed consumption under the maintained model and annual observation frequency. As with structural estimates more generally, their precise behavioral interpretation may also reflect differences in expectations, uncertainty, and social context.

A growing body of evidence in economics finds that adolescents discount future rewards much more steeply than adults and that patience increases markedly with age during the

transition to adulthood (e.g., Sutter et al. 2013; Golsteyn et al. 2014). Direct comparisons of younger and older individuals document a substantially lower willingness to delay gratification among adolescents, and show that these early-life time preferences predict important long-run outcomes such as educational attainment, health behaviors, and labor-market success (Golsteyn et al. 2014; Alan and Ertac 2018). While these studies typically rely on experimental or behavioral elicitation rather than structural Euler-equation estimation, they consistently point to substantially greater impatience early in the life cycle, broadly consistent with the pattern observed here. Because such measures capture short-horizon delay discounting rather than annual intertemporal trade-offs, their parameters are not numerically comparable to our δ estimated within the rational addiction framework.

5 Discussion and conclusion

This paper tests whether young and adult smokers differ in their time preferences, particularly with respect to present bias, using longitudinal data on individual cigarette consumption. We find no evidence of present bias in either group and obtain estimates consistent with forward-looking, rationally addictive behavior. Young smokers nevertheless have a substantially lower estimated long-run discount factor than adults.

One possible explanation for the absence of estimated present bias concerns the time horizon implicit in our data. Present bias, as formalized in quasi-hyperbolic models, reflects a disproportionate weight placed on immediate utility relative to all future periods, and is most naturally identified in short-horizon trade-offs (e.g. today versus tomorrow) (O'Donoghue and Rabin 2015). In contrast, our empirical specification relies on annual observations and therefore captures intertemporal trade-offs over one-year intervals. If present bias primarily manifests at very short horizons—such as daily or weekly decisions—annual data may smooth over these short-run discontinuities and instead identify a long-run dis-

count factor. In this sense, our estimates should be interpreted as reflecting medium- to long-term impatience rather than ruling out short-horizon present bias altogether.

This limitation suggests caution in interpreting the absence of $\beta < 1$ as definitive evidence against self-control problems. It remains possible that present bias operates at higher frequencies than our data allow us to detect. At the same time, annual observations are well suited to studying addictive behaviors such as smoking, whose health consequences, habit formation, and cessation dynamics unfold over longer horizons; thus the data allow us to identify life-cycle differences in medium- and long-run discounting that are central to understanding persistent consumption patterns, even if very short-run fluctuations in self-control remain unobserved. Future research using higher-frequency panel data—such as weekly or monthly measures of consumption, cessation attempts, or relapse behavior—would provide a more direct test of short-run present bias and could complement the life-cycle perspective adopted here.

While we do not find evidence of present bias in the sense of quasi-hyperbolic discounting (i.e., $\beta < 1$), we document substantially higher discount rates among younger individuals. This distinction is important. Present bias refers to a specific form of time inconsistency in which immediate outcomes receive disproportionate weight relative to all future periods. Exponential discounting, by contrast, implies dynamically consistent preferences: individuals apply a constant discount factor to future utilities, and their intertemporal trade-offs do not change over time. Our results therefore point to stronger impatience among young smokers as the primary pattern detectable in annual consumption data, without ruling out self-control problems operating at shorter horizons.

The absence of present bias does not eliminate the relevance of age differences in discounting. When discount rates differ systematically across age groups, individuals who make decisions at younger ages do so under preferences that place substantially less weight on future outcomes. In the context of addictive goods, early consumption involves partially

irreversible investments in habit formation and health capital. Even when behavior is dynamically consistent at each point in time, differences in long-run discounting can lead to divergent lifetime outcomes across cohorts exposed to addictive goods at different ages.

This perspective is consistent with life-cycle models in which impatience is age-dependent (Crettez and Deloche 2021) and with experimental evidence documenting steeper discounting among younger cohorts without detecting quasi-hyperbolic present bias (Freeman and Laughren 2024). The findings therefore shift the emphasis from detectable time inconsistency at the annual horizon to the interaction between high youth discount rates, the persistence of addiction, and the long horizon over which health consequences materialize.

Age-based regulations such as Tobacco 21 may be interpreted within this framework as instruments that delay exposure to addictive goods during the period in which discounting is steepest. Our results do not provide evidence on the causal effectiveness of such policies, nor do they imply that young smokers suffer from time inconsistency or naiveté. Rather, they suggest that age heterogeneity in exponential discounting may contribute to differences in vulnerability to long-run health costs. In this sense, our findings inform the theoretical debate on the behavioral foundations of age-based regulation, without directly evaluating its welfare consequences or empirical impact.

To move beyond the quasi-hyperbolic framework, future theoretical and empirical research should explore alternative models capable of capturing life-cycle heterogeneity and the shifting nature of intertemporal trade-offs. One promising avenue is the adoption of age-varying discount rates; recent evidence suggests that discount rates decline linearly over the life cycle, which can explain broad behavioral shifts—such as undersaving when young and oversaving when old—without invoking present bias (Kureishi et al. 2021). Furthermore, heterogeneity in time preferences remains significant even at older ages, heavily influencing wealth, health investments, and retirement decisions (Huffman et al. 2019; Bozio et al. 2017). Another compelling framework involves non-stationary or time-varying preferences.

Models like the nested exponential discount function demonstrate that preference drift and time-variance can often explain time-inconsistent choices far better than traditional quasi-hyperbolic discounting (Holloway et al. 2025). Finally, to account for the common phenomenon of individuals wishing they had consumed less of an addictive good in their youth, theoretical work could leverage models featuring backward discounting, which generate regret over past decisions while maintaining dynamically consistent, forward-looking behavior (Caliendo and Findley 2020). Integrating these alternative frameworks—age-dependent impatience, time-varying preferences, and dynamic consistency with regret—into models of addiction offers a rich agenda for future research into how shifting evaluations of utility shape lifetime consumption trajectories.

5.1 Context and external validity

Russia provides a distinctive institutional and epidemiological setting for studying smoking behavior. Adult smoking prevalence has historically been high by international standards, and although tobacco control policies strengthened following Russia's ratification of the WHO Framework Convention on Tobacco Control in 2008, substantial regional variation persists in prices, affordability, and cessation outcomes (Zasimova and Kolosnitsyna 2025). These features raise legitimate questions about the external validity of our findings, particularly for countries such as the United States, where smoking prevalence has declined earlier and more sharply.

Comparative surveillance data highlight this divergence. Cigarette use among adolescents has become relatively uncommon in the United States, whereas available Global Tobacco Surveillance System (GTSS) evidence indicates higher rates of youth tobacco involvement in Russia. Among adults, the 2016 Global Adult Tobacco Survey reports that 29.9% of Russian adults smoke, with most smokers consuming cigarettes daily and averaging roughly 16 cigarettes per day (WHO 2018). In contrast, U.S. data show both lower

prevalence and a long-term shift toward lighter smoking patterns. Thus, Russian smokers –both young and adult– are embedded in an environment where smoking remains more prevalent and socially visible.

These contextual differences may influence intertemporal decision-making in several ways. First, when a behavior is common and socially normative, its immediate utility may be reinforced by peer effects, potentially amplifying present-oriented choices independently of individual discount rates. Second, higher affordability and historically weaker tobacco control may reduce the perceived future cost of smoking, attenuating incentives for forward-looking behavior. Third, later diffusion of strong anti-smoking information campaigns may alter how health risks enter individuals' expectations about the future.

For these reasons, our estimates should be interpreted as evidence on age-related differences in time preferences within a high-prevalence smoking environment rather than as universally applicable magnitudes. At the same time, precisely because smoking remains widespread among Russian youth relative to many Western countries, the setting provides a useful context in which to identify behavioral mechanisms linking age and intertemporal choice. Cross-country differences are therefore likely to affect the level of estimated discounting, but less the qualitative insight that younger individuals exhibit stronger present orientation.

In sum, annual consumption data provide no evidence of quasi-hyperbolic present bias in either age group, but reveal a pronounced age gradient in long-run discounting. This gradient persists across the selected alternative age windows, pointing to substantial age-related heterogeneity in patience that models imposing a common long-run discount factor across ages would obscure. As with structural estimates more generally, its precise behavioral interpretation depends on the maintained rational-addiction framework, the annual frequency of observation, and the Russian smoking environment. The results therefore point to stronger impatience among young smokers, rather than detectable time inconsistency at

the annual horizon, as a potential source of vulnerability to addictive consumption.

Statements and declarations

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Data availability: *The data used in this study are drawn from Waves 5–29 (1994–2020) of the Russia Longitudinal Monitoring Survey–Higher School of Economics (RLMS-HSE). The public-use individual, household, and community data, together with the corresponding questionnaires and documentation, are publicly available through the official RLMS-HSE data portal. The Stata code used for data preparation and estimation is available on the journal page.*

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A Appendix

A.1 Choice of instrumental variables

We need a set of instruments Z_{it} that are uncorrelated with the first-differenced error term Δu_{it} and correlated with the regressors. By definition

$$\Delta u_{it} = \xi_1 \Delta e_{it} + \xi_2 \Delta e_{it+1} + \beta\delta\Delta r_{it+1} \tag{8}$$

for $i = 1, ..., N$ and $t = 3, ..., T-1$. Given (8), the following moment conditions are available: $E(C_{it-s}\Delta u_{it}) = 0$ for $t = 4, ..., T-1$ and $s \geq 3$. This allows the use of lagged levels of the observed consumption series dated $t-3$ and earlier as instruments for the first-differenced equation (9):

$$\Delta C_{it} = \phi_1 \Delta C_{it-1} + \phi_2 \Delta C_{it+1} + \phi_3 \Delta P_{it} + \phi_4 \Delta P_{it-1} + \phi_5 \Delta P_{it+1} + \phi_6 \Delta X_{it} + \phi_7 \Delta d_t + \Delta u_{it} \tag{9}$$

The moment restrictions can be written in matrix form as $E(Z_i'\Delta u_i) = 0$ for $t = 4, ..., T-1$, where Δu_i is the $(T-4)$ vector $(\Delta u_{i4}, \Delta u_{i5}, ..., \Delta u_{iT-1})'$. $\Delta u_i = u_{it} - u_{it-1}$ and Z_i is a $(T-4) \times g$ block diagonal matrix, whose i^{th} block is:

$$Z_i = \begin{pmatrix} C_{i1}, P_{i1}, P_{i2} & 0 & 0 & \dots & 0 & \dots & 0 & \Delta W_{i4}' \\ 0 & C_{i1}, P_{i1}, P_{i2} & C_{i2}, P_{i2}, P_{i3} & \dots & 0 & \dots & 0 & \Delta W_{i5}' \\ \vdots & \vdots & \vdots & \dots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & \dots & C_{i1}, P_{i1}, P_{i2} & \dots & C_{iT-4}, P_{iT-4}, P_{iT-3} & \Delta W_{iT-1}' \end{pmatrix}.$$

where the block diagonal structure at each time period exploits all of the instruments available, concatenated to one-column of first differenced exogenous regressors $\Delta W_{it}' = (\Delta X_{it})$ that act as instruments for themselves (Arellano and Bond 1991).

As mentioned in the main text, the First Differences GMM estimator behaves poorly in finite samples when instruments are weak. System GMM (Blundell and Bond 1998)

delivers better finite sample properties by exploiting additional moment conditions which are valid under the correlated effects assumption. This yields $(T-4)$ further linear moment conditions, $E(\Delta C_{it-2}u_{it}) = 0$ for $t = 4, ..., T-1$, which allow the use of equations in levels with suitably lagged first-differences of the series as instruments. The complete system of moment conditions available can be expressed as $E(Z_i^{+'}u_i^+) = 0$, where $u_i^+ = (\Delta u_{i4}, ..., \Delta u_{iT-1}, u_{i4}, ..., u_{iT-1})'$.

The instrument matrix, Z_i^+, for this system is

$$Z_i^+ = \begin{pmatrix} Z_i & 0 & 0 & \dots & 0 \\ 0 & \Delta C_{i2}, \Delta P_{i3} & 0 & \dots & 0 \\ 0 & 0 & \Delta C_{i3}, \Delta P_{i4} & \dots & 0 \\ \vdots & \vdots & \vdots & \dots & \vdots \\ 0 & 0 & 0 & \dots & \Delta C_{iT-3}, \Delta P_{iT-2} \end{pmatrix}$$

where the first row is the set of valid instrument for the equation at time $t = 4$.

In finite samples, such a large collection of instruments generates a bias/efficiency trade-off (Biørn and Klette 1998; Roodman 2009a; Ziliak 1997). For this reason, after experimenting with the instruments, we use in our preferred specifications (Table 2) two parsimonious matrices of instruments, Z_i^Y and Z_i^A, for the equations for the young and adult samples, respectively, where we use only a subset of the available instruments, discarding the use of some valid ones either by collapsing or curtailing the instrument matrix (Kiviet 2020).

A.2 Restricted model estimation

One possible issue in estimating the general version of the Rational Addiction model when assuming $\beta = 1$, as supported by our results, is overparametrization. The problem is that the same structural parameters would be derived by different empirical parameters. More specifically, the discount factor would be obtained by the ratios $\frac{\phi_F}{\phi_L}$ and $\frac{\varphi_F}{\varphi_L}$, with no

guarantee that the result is identical, and generally will not. One possibility, would be to constrain one of the parameters, although this is not easily achievable using available statistical programs and commands. Most of the empirical literature, instead, facing difficulties in properly estimating the general version of the RA model, resorted to the restricted version. The restricted specification excludes lagged and lead prices. From a theoretical perspective, this amounts to assuming complete depreciation of the addiction stock within each annual period, that is, $\gamma = 1$ in equation (2). Although this is a strong assumption given the persistence of addiction, it allows us to recover the discount factor from the ratio of the lead to lagged consumption coefficients and avoids overparameterization. This may be reasonably considered implausible, knowing how persistent addiction can be in the real world. However, this specification still allows us to recover the discount factor as $\frac{\phi_F}{\phi_L}$, avoids overparametrization, and, considering smoking addiction and that our time period is one year, it may not be completely unreasonable assuming that in one time period addiction fully depreciates.[11]

Thus, to check the robustness of our results we also estimate the restricted version of the RA model on the samples of youths and adults with the same set of covariates. The results, presented in Table A1 are indeed very close to those obtained for the general specification. In particular, with the restricted specification, the discount factor for youths is just 1% smaller than with the general specification, and that of adults 2% larger, confirming our main result.

[11]This would mean that a smoker that stops smoking today and never smokes for one year could be considered addiction free at the end of the period.

Table A1: Restricted model estimation

	Young (age $\leq$ 21)	**Adults** (30 $\leq$ age $\leq$ 65)
C_{t-1}	0.361***	0.497***
	(0.074)	(0.057)
C_{t+1}	0.194***	0.492***
	(0.076)	(0.063)
P_t	-0.044*	-0.010**
	(0.023)	(0.0048)
Discount factor	0.538	0.988
Discount rate	0.859	0.012
Short-run elasticity	-0.136	-0.028
	(0.066)	(0.015)
Long-run elasticity	-0.310	-2.424
	(0.167)	(1.795)

Notes: Robust SE in parentheses below coefficients. Standard errors for the elasticities are computed using the delta method. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.