Estimating Biases in Smoking Cessation:

Evidence from a Field Experiment

Justin S. White

University of California, San Francisco

Joint with:

Frank J. Chaloupka, University of Illinois-Chicago

Matthew R. Levy, London School of Economics

TOPS, November 12, 2021

Disclosures

- Funding: This study was funded by the National Institute on Drug Abuse under Award Number P50 DA036128 (PI: Michael Eriksen).
- Disclaimer: The content is solely the responsibility of the authors and does not necessarily represent the official views of the NIH.
- I have no other competing interests to disclose. My co-authors and I have never received funding from the tobacco-nicotine industries.
- The experiment was registered in the AEA RCT Registry (Protocol # AEARCTR-0002106) and approved by the University of Illinois-Chicago IRB (Protocol # 2013-0844).

Outline

Introduction

Research questions

1. To what extent do individuals make biased decisions about smoking cessation?
   - "Biases" refers here to decisions or beliefs that deviate from rational choice, in part as a manifestation of addiction.
   - Our focus: behavioral biases suggested in the behavioral economics literature.
2. What do the biases imply for the welfare of individuals who smoke?
   - Determine the value of the loss in welfare ("pleasure") due to biased smoking decisions, in terms of utility and money.

Why measure biases and welfare?

1. Input into a regulatory impact analysis (RIA) or cost-benefit analysis of tobacco policies
   - US federal agencies including the FDA are required to assess costs and benefits of major regulatory actions and to select the one with greatest net benefit (Clinton 1993, Obama 2011).
   - RIAs of tobacco regs should consider costs of any biases.
2. Improved understanding of (smoking) behavior
3. Selection of policies/interventions for smoking cessation
   - Policy proposals depend on our theory of smoking behavior.
   - Here, we move away from a rational addiction model and its focus on smoking externalities to examine "internalities," the costs smokers impose on themselves

Estimating costs of regulations affecting addictive goods

Regulations can impose costs on individuals.

- For most goods, when a regulation leads people to change behavior, RIA considers the benefits of behavior change versus its costs known as “lost consumer surplus.”

- For addictive goods like smoking, do we offset the health benefits from tobacco regulations with the lost pleasure to smokers who quit? How?
  - Researchers have disagreed about the best way to account for addiction and possible internalities (Levy 2018)
  - Estimates of the lost pleasure offset has varied widely, e.g., from 10-99% of health benefits of quitting (Ashley 2015, Cutler 2015)

Ways to estimate net benefits of regulations

1. Willingness to pay (WTP) for smoking cessation
   - Amount willing to pay for product like Chantix $\Rightarrow$ benefits exceed that cost, but WTP valuations may be biased too.
2. Direct measurement of subjective well-being
3. Rational benchmark
   - Define a "rational" group of smokers (e.g., college-educated or less addicted smokers) (e.g., Cutler 2015, Jin 2015, Levy 2018)
4. Structural approaches
   - Start with a specific behavioral model.
   - Choosing values of "structural parameters" (e.g., for behavioral biases) is dicey and often based on calibration exercises (Gruber 2001).

Source: Cutler et al. (2016), *AJPM*

Study aim

We ran a randomized field experiment to obtain structural estimates for 3 key biases that may afflict smokers:

1. Present-biased preferences
2. Naïve beliefs regarding present bias
3. Projection-biased beliefs over future abstinence

All three represent departures from rationality.

The experiment minimizes the need for arbitrary assumptions in estimating the structural model (DellaVigna 2018).

1. Present-biased preferences

- Imperfect self-control
  - Over-weighting the immediate pleasure from satisfying a craving or avoiding withdrawal symptoms at the expense of future health and financial benefits
- Modeled as an extra discount factor β applied to utility in the future vs. now (Laibson 1997)
  - $\beta = 1$: No extra discounting of the future (time-consistent)
  - $\beta < 1$: Extra discounting of the future (time-inconsistent, present-biased)
- Suggestive evidence of present bias includes use of pre-commitments, high time and delay discounting rates (Wertenbroch 1998, Giné 2010, Halpern 2015, White 2020, Bickel 1999, Chabris 2008)

2. Naïve beliefs about present bias

Agents differ in awareness of their future self-control.

- *Sophisticates* are self-aware; *naïfs* are not
- Welfare loss may be especially large for naïfs who fail to correct a problem they don't recognize
  - e.g., delay a quit attempt today b/c expect to do it tomorrow
- Suggestive evidence of naïveté, e.g., widespread regret of starting to smoke, high relapse rates (Fong 2004, Hughes 2004).
- Degree of naïveté modeled as $\tilde{\beta}$, belief about one's future self-control (O'Donoghue 1999)
  - Naïve: overestimating one's self-control ($\tilde{\beta} < \beta$)

3. Projection-biased beliefs

Projecting how you feel now onto how you think you'll feel in the future when in a different visceral "state" (Loewenstein 2003; 2005)

Two flavors for smoking:

1. Short-term fluctuations in craving
   - In low-craving state, may fail to anticipate behavior in high-craving state $\Rightarrow$ overestimate future willingness to abstain
2. Longer-term transition from addicted to not addicted
   - In addicted state, may fail to predict how preferences will change once not addicted $\Rightarrow$ underestimate benefits of quitting and subsequent willingness to abstain.

3. Projection-biased beliefs

Projecting how you feel now onto how you think you'll feel in the future when in a different visceral "state" (Loewenstein 2003; 2005)

Two flavors for smoking:

1. Short-term fluctuations in craving
   - In low-craving state, may fail to anticipate behavior in high-craving state $\Rightarrow$ overestimate future willingness to abstain
2. Longer-term transition from addicted to not addicted
   - In addicted state, may fail to predict how preferences will change once not addicted $\Rightarrow$ underestimate benefits of quitting and subsequent willingness to abstain.

We focus on #2, embedding a smoking cessation intervention in the experiment to induce a change in addiction state.

Preview of findings

- Smokers substantially over-estimate their future abstinence
  - 100% of sample is present-biased (avg $\beta = 0.67$)
  - Subjects partially aware of present bias (avg $\tilde{\beta} = 0.85$)
  - Substantial heterogeneity in biases
- Our abstinence intervention increases likelihood of future abstinence, but on average:
  - Ex-ante, subjects do not anticipate any effect $\rightarrow$ highly projection-biased
  - Ex-post, subjects believe effect (marginally) negative
- Continuing to smoke is “efficient” under present bias and when addicted, but reduces welfare $\$414$ per week after accounting for present bias and projection

Contributions

1. A novel lottery-based approach for remote monitoring of smoking status that is strictly incentive-compatible (i.e., incentivizes accurate reporting)
2. Experimentally-identified estimates of smoking biases based on willingness to pay for partial commitment devices (Acland 2015, Carrera 2019)
3. Field evidence on the magnitude and nature of the welfare loss of smoking
4. Within-subject comparison across multiple biases

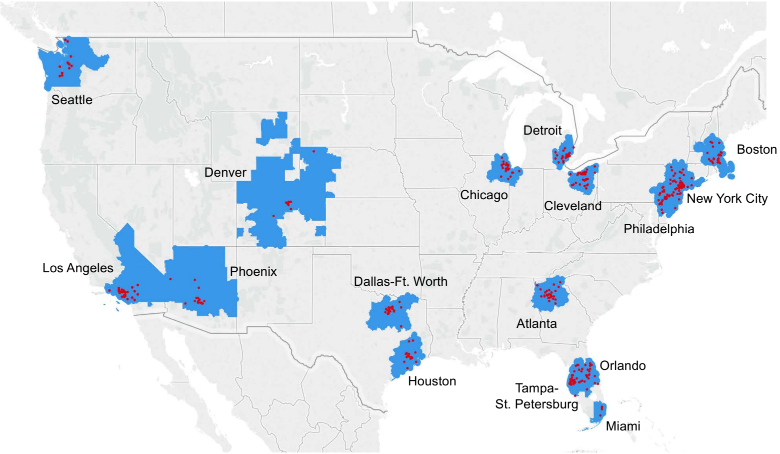
Experimental design

Recruitment and eligibility

- Individual-level field experiment over 3 months (12 weeks)
- 397 cigarette smokers from 16 large US metro areas, recruited from a web-based panel
- Key eligibility criteria
  - Age 21 and over
  - Smoked cigarettes $\geq$ 20 of prior 30 days
  - Access to smartphone or tablet camera
  - Agreed to in-person study visits
  - Verified as smoker using saliva cotinine test

We do not screen on quit expectations.

Zip codes from target metro areas



Note: This map shows targeted zip codes in blue ($N = 8,820$), along with the name of the targeted metro areas, and subjects' zip codes as red dots.

A tale of several randomizations

1. Predictions, valuations about future abstinence incentives
   - 3 sessions: baseline, end of Month 1, end of Month 2
   - Randomize: incentive amounts ($10-400), week in Month 3
2. Abstinence incentives
   - One/person in Month 1, one/person in Month 3
   - Randomize: incentive amounts ($10-400), week
3. Smoking cessation intervention
   - In Month 2, up to $100/week in abstinence incentives, web-based support
   - Random 67% of sample ("treated group")

How to remotely verify smoking status? (1)

- Positive saliva cotinine test required to qualify for study
  - Screens out (many) non-smokers
  - Selects for people who can do the saliva test
  - Gives facial image to compare against in later stages
- Cotinine tests mailed to subjects following baseline
- Series of 3 photos uploaded

Photo 1: swabbing

Photo 2: test result

Photo 3: blacked-out window

How to remotely verify smoking status? (2)

- 3-step verification during 12-week study period
  1. Weekly online survey of self-reported 7-day abstinence
  2. Weekly saliva test for those eligible for abstinence incentives and random subset of others
  3. In-person visits to audit random subset of saliva tests
- Two weekly "truth-telling" lotteries to get accurate smoking reports
  1. \$50 lottery (1 per week) if self-report matches saliva test $\rightarrow$ incentivizes accurate reporting
  2. \$100 lottery (1 per week) if report abstinence, verified by saliva test $\rightarrow$ preferable to be (and report being) abstinent

How to measure real-world biases? (1)

Present bias and naïveté

- Ask subjects how much they would pay for future incentives to abstain. Do so in a way that incentivizes accurate reports.
- Offer cash incentives for future abstinence.
  - One in random week of M1 (trial run) and one in M3.
  - Payment of $10 to $400.
  - Paid if (a) report 7-day abstinence, (b) negative saliva test
- Compare the valuations to the real-world smoking behavior to test for over-optimism (present bias and naïveté).

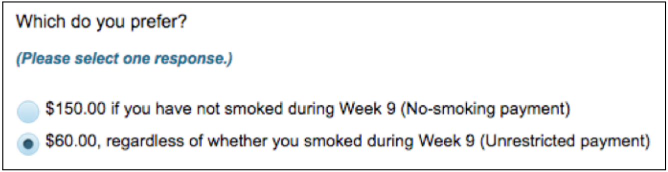
How to measure real-world biases? (2)

Projection bias

- Randomly assign 67% of sample to receive a smoking cessation intervention in Month 2 ("treated" group).
  - Up to $100 per week in abstinence incentives and referred to web-based support (Smokefree.gov and becomeanex.org).
- Creates exogenous $\uparrow$ in abstinence
- Compare valuations of future abstinence incentives between treated and control subjects before vs. after Month 2 intervention (the change in addiction state) to test for projection bias.

Valuations of future abstinence incentives

- In each of 3 sessions, elicit valuations of future abstinence incentives in a target week in M3
- Ask 3-4 "staircase" choice questions b/w future abstinence incentive p of \$10-400 and non-contingent payment q of $0.1p$ to $1.1p$


Which do you prefer?

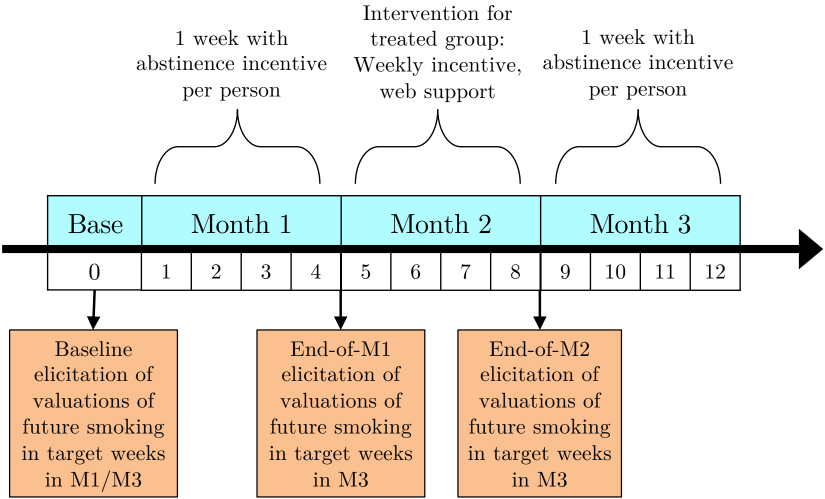
(Please select one response.)

- [ ] \$150.00 if you have not smoked during Week 9 (No-smoking payment)
- [x] \$60.00, regardless of whether you smoked during Week 9 (Unrestricted payment)

- Randomize starting point; 12 possible outcome ranges
- Complete 4 staircases for different p and weeks per session
- Randomly select 1 subject $\times$ week $\times$ q, give (implied) choice from row
- Also elicit *stated predictions* of future abstinence for each staircase $\rightarrow$ predicted probability would abstain for p in target week

Staircase

Experimental design



Note: During one week of Month 1 and one week of Month 3, each subject was eligible for one abstinence incentive payment. Month 2 is the treatment month.

Experimental (reduced-form) results

Key hypotheses for reduced-form analysis

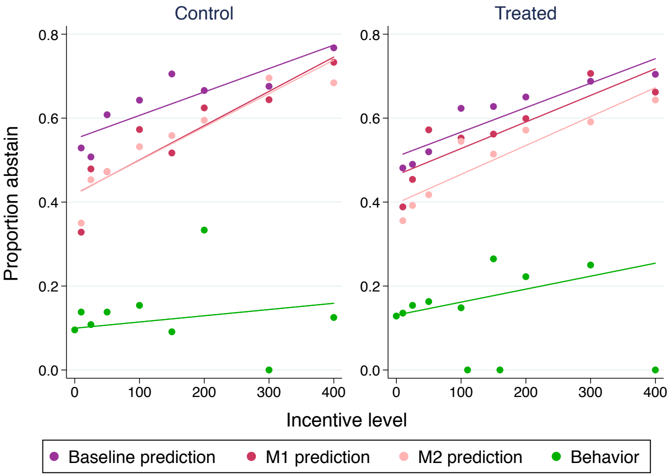
1. Treatment month (Month 2) increased abstinence in treated vs. controls.
2. Subjects are over-optimistic about willingness to abstain in a future week relative to observed abstinence.
   - Compare abstinence valuations/predictions vs. behavior
3. Subjects mispredict the effect of cessation intervention on their subsequent willingness to stay abstinent (projection bias).
   - Double-difference in predictions before vs. after treatment month for treated vs. control group

Baseline characteristics

	All	Control	Treated	p-value of diff.
Male (%)	34	29	36	0.16
Age (%)				
21-34	24	29	21	0.17
35-44	27	27	27	0.98
45-54	29	27	31	0.34
≥ 55	20	17	21	0.55
Race/ethnicity (%)				
Non-Hispanic White	75	70	77	0.10
Non-Hispanic Black	13	14	12	0.33
Hispanic	8	10	7	0.27
Household income (%)				
$<$ \$30,000	25	29	23	0.29
\$30,000 - \$49,999	21	18	23	0.24
\$50,000 - \$99,999	36	38	35	0.60
$\geq$ \$100,000	17	15	18	0.36
Mean cigarettes per day	15	15	15	0.88
Nicotine dependent (%)	56	58	55	0.54
Planning to quit $<$ 6 months (%)	33	30	35	0.31
E-cigarette use in last 30 days (%)	26	30	24	0.29
No. observations	397	132	265	
p-value from joint F-test				0.89

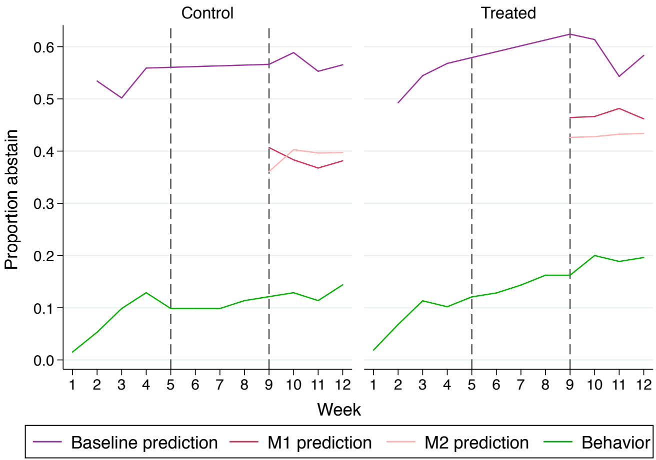
Note: p-values are reported for Wald tests on the equality of means of treatment and control groups for each variable.

Abstinence behavior and predictions by incentive level and treatment group



Note: This figure shows the average abstinence behavior or predictions by incentive level and treatment group. The left panel is for the control group, and the right is for the treated group.

Abstinence behavior & predictions by week



Note: This figure shows the average abstinence behavior or average predictions from each survey (unincentivized), by study week and treatment group. Weeks in which a subject was eligible for a smokefree-contingent payment are included. The left panel is for the control group, and the right is for the treated group.

Effect of M2 treatment on abstinence

(1) $Abstain_{it} = \alpha + \beta(Treat_i \times M3_t) + \gamma Treat_i + \delta M3_t + \mu_t + \lambda_i + \varepsilon$ for person i in week t

	Dep. var.: weekly abstinence	
	(1)	(2)
Month 3	0.122***	0.122***
	(0.024)	(0.024)
Treated × Month 3	0.058**	0.058**
	(0.026)	(0.026)
Month 2		0.105***
		(0.021)
Treated × Month 2		0.035
		(0.022)
Constant	0.018	0.018
	(0.012)	(0.013)
R^2	0.06	0.05
N	3,176	4,764
Week FE	Yes	Yes
Individual FE	Yes	Yes

5.8 percentage point ↑ in abstinence

⇒ treated group is relatively less addicted following treatment month

Note: SEs, clustered by person, are in parentheses. Model 1 includes data from Months 1 and 3 only. Model 2 includes data from all months. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Difference between observed and predicted abstinence (Over-optimism)

	Dep. var.: weekly abstinence	
	(1)	(2)
Behavior $= 1$	-0.429***	-0.314***
	(0.026)	(0.028)
Incentive		0.076***
		(0.009)
Behavior $\times$ Incentive		-0.050***
		(0.014)
Constant	0.533***	0.415***
	(0.020)	(0.023)
R^2	0.39	0.42
N	2,024	2,024
Individual FE	Yes	Yes

Predicted abstinence 42.9 points ↓ than observed abstinence

$\Rightarrow$ severe over-optimism

Note: Control group only. Data set stacks observed abstinence behavior on top of abstinence predictions. Regresses an indicator of weekly abstinence on *Behavior* = 1 for observed abstinence and 0 for predictions. Incentives scaled in \$100s. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Difference between observed and predicted abstinence (Over-optimism)

	Dep. var.: weekly abstinence	
	(1)	(2)
Behavior $= 1$	-0.429***	-0.314***
	(0.026)	(0.028)
Incentive		0.076***
		(0.009)
Behavior $\times$ Incentive		-0.050***
		(0.014)
Constant	0.533***	0.415***
	(0.020)	(0.023)
R^2	0.39	0.42
N	2,024	2,024
Individual FE	Yes	Yes

5.0 point ↑ in over-optimism for each additional $100

Note: Control group only. Data set stacks observed abstinence behavior on top of abstinence predictions. Regresses an indicator of weekly abstinence on *Behavior* = 1 for observed abstinence and 0 for predictions. Incentives scaled in $100s. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Difference-in-differences of predictions (Projection bias)

	(1)
Baseline predictions	0.101***
	(0.022)
End-of-M2 predictions	0.005
	(0.018)
Baseline predictions × Treated	-0.044
	(0.028)
End-of-M2 predictions × Treated	-0.049**
	(0.023)
Constant	0.504***
	(0.015)
N	4,009
Week FE	Yes
Individual FE	Yes

Predicted abstinence revised ↓ after treatment by 4.9 points for treated vs. control subjects

⇒ consistent with treated group projecting cravings onto M3 utility

Note: Dep. var. is an indicator of predicted weekly abstinence. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Structural estimation

Sketch of structural model

- We estimate a structural model with key parameters:
  - Utility parameters: weekly disutility of abstinence (c), discounted long-run benefit of abstinence (δb), utils/dollar (γ)
  - Treatment effect and predictions: treatment effect, ex-ante beliefs about treatment effect in M1 ($\tilde{\eta}_1$), ex-post beliefs about treatment effect in M3 ($\tilde{\eta}_2$)
  - Discount parameters: present bias (β), degree of naïvete ($\tilde{\beta}$)
- After the treatment month, treated subjects receive utility from abstinence equal to:

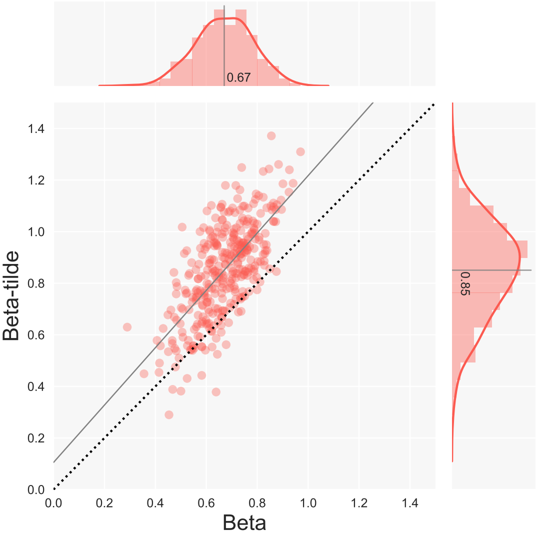
$$U(abstain) = \eta + \beta\delta b + \gamma p - c$$

- Valuations decompose into cash value and commitment value provided by the incentive, allowing for separate identification of present bias and naïveté.
- Estimate by maximum likelihood using M2, M3 abstinence data.

Structural parameters

Description	Parameter	Est. (utils)	Est. ($)
Weekly disutility of abstinence	μ_c	8.883^{***}	$8,075
Discounted long-run benefit of abstinence	b	8.783^{***}	$7,985
Utils per dollar	γ	0.001	
Scale parameter	σ	0.105^{***}	
Treatment effect	η	0.555^{***}	$505
Beliefs about treatment effect in M1	$\tilde{\eta}_1$	0.126	$115
Beliefs about treatment effect in M3	$\tilde{\eta}_2$	-0.084	-$76
Present bias (mean)	$\bar{\beta}$	0.670^{***}	
Degree of naïvete (mean)	$\bar{\tilde{\beta}}$	0.851^{***}	

Present bias β vs. naïveté $\tilde{\beta}$



1. 100% of subjects are present-biased ($\beta < 1$) mean β = 0.67

2. $\tilde{\beta}$ in partial sophistication range, mean $\tilde{\beta} = 0.85$

   92% have $\tilde{\beta} > \beta$

   80% have $\tilde{\beta} < 1$

3. Regression line: $\tilde{\beta} = 0.11 + 1.11\beta$, $R^2 = 0.46$

Projection bias

- Before the treatment month, subjects underestimate the value of the treatment (0.13 utils vs. actual 0.56 utils)

  $\rightarrow$ we fail to reject that subjects completely project their addicted state onto predictions of the future benefits of abstinence

- After the fact, subjects mispredict even more badly, believing that abstinence lowered their utility. Not consistent with simple projection bias.

Welfare calculations

- From perspective of a present-biased smoker, there is a strong preference to continue smoking ($\beta b - c = -2.83$ utils)
- Correcting present bias only (setting $\beta = 1$), smoking is roughly welfare neutral and yields no internality ($b - c = -0.01$ utils)
- Correcting present bias and projection bias, smoking induces private welfare loss of $\$414$/week ($b - c + \eta = 0.45$ utils)
  - Dividing by average baseline smoking yields $\$80$/pack
  - Present bias $\downarrow$ value of quitting by \$2,635, projection bias by \$390
- Our welfare calculations imply that a sales ban on cigarettes would increase a smoker's welfare by at least \$353 per week.

Conclusions

Conclusions

- We find a pernicious pattern of biased beliefs, not rationalizable under a standard model of rational addiction
  - On average highly present biased and substantially naive: mean $\beta = 0.67$, mean $\tilde{\beta} = 0.85$
  - Failure to reject complete projection bias prior to intervention
  - After intervention, projection of craving/withdrawal $\rightarrow$ a model of simple projection bias may be too simple
- *Under their own long-run preferences*, smokers' choices lead to a large private welfare loss.
  - Accounting for both intertemporal and state-dependent mispredictions is critical.
- A sales ban on cigarettes, as pursued by a handful of localities to date, may be welfare enhancing.

Conclusions

- RIAs need to incorporate internalities in order to reflect smoking decisions.
- Policy Interventions also might account for biased smoking decisions.
  - Use of precommitments
  - Incentives with escalating reward schedule (Higgins 2014)
  - Focus on smoking prevention
- Our findings (notably 100% present-biased smokers) underscore the challenge of using a rational benchmark approach to calculating lost pleasure.
- We show feasibility of a novel method of remotely monitoring smoking in an incentive-compatible way.
  - Though unclear incentive-compatibility always needed (Buckell 2020)
- We measure smoking biases using experimental variation and a new identification strategy.

Thank you

justin.white@ucsf.edu

Extra Slides

References I

Acland, Dan and Matthew R Levy, "Naiveté, projection bias, and habit formation in gym attendance," *Management Science*, 2015, *61* (1), 146–160.

Ashley, Elizabeth M, Clark Nardinelli, and Rosemarie A Lavaty, "Estimating the benefits of public health policies that reduce harmful consumption," *Health Economics*, 2015, *24* (5), 617–624.

Bickel, Warren K, Amy L Odum, and Gregory J Madden, "Impulsivity and cigarette smoking: delay discounting in current, never, and ex-smokers," *Psychopharmacology*, 1999, *146* (4), 447–454.

Buckell, John, Justin S. White, and Ce Shang, "Can incentive-compatibility reduce hypothetical bias in smokers' experimental choice behavior? A randomized discrete choice experiment," *Journal of Choice Modelling*, 2020, *37*, 100255.

Carerra, Maria, Heather Royer, Mark Stehr, Justin Sydnor, and Dmitry Taubinsky, "How are preferences for commitment revealed?," August 2019. Mimeo.

Chabris, Christopher F, David Laibson, Carrie L Morris, Jonathon P Schuldt, and Dmitry Taubinsky, "Individual laboratory-measured discount rates predict field behavior," *Journal of Risk and Uncertainty*, 2008, *37* (2-3), 237.

Cutler, David M., Amber I. Jessup, Donald S. Kenkel, and Martha A. Starr, "Economic Approaches to Estimating Benefits of Regulations Affecting Addictive Goods," *American Journal of Preventive Medicine*, 2016, *50* (5, Supplement 1), S20 – S26. The Use of Economics in Informing U.S. Public Health Policy.

__ , Amber Jessup, Donald Kenkel, and Martha A. Starr, "Valuing Regulations Affecting Addictive or Habitual Goods," *Journal of Benefit-Cost Analysis*, 6 2015, *6*, 247–280.

References II

DellaVigna, Stefano, "Structural Behavioral Economics," in B. Douglas Bernheim, Stefano DellaVigna, and David Laibson, eds., *Handbook of Behavioral Economics*, Vol. Volume 1, North-Holland, 2018, chapter Chapter 7, pp. 613–723.

Fong, Geoffrey T, David Hammond, Fritz L Laux, Mark P Zanna, K Michael Cummings, Ron Borland, and Hana Ross, "The near-universal experience of regret among smokers in four countries: findings from the International Tobacco Control Policy Evaluation Survey," *Nicotine & Tobacco Research*, 2004, *6* (Suppl_3), S341–S351.

Giné, Xavier, Dean Karlan, and Jonathan Zinman, "Put your money where your butt is: a commitment contract for smoking cessation," *American Economic Journal: Applied Economics*, 2010, *2* (4), 213–35.

Gruber, Jonathan and Botond Kőszegi, "Is Addiction "Rational"? Theory and Evidence," *Quarterly Journal of Economics*, November 2001, *116* (4), 1261–1303.

Halpern, Scott D., Benjamin French, Dylan S. Small, Kathryn Saulsgiver, Michael O. Harhay, Janet Audrain-McGovern, George Loewenstein, Troyen A. Brennan, David A. Asch, and Kevin G. Volpp, "Randomized Trial of Four Financial-Incentive Programs for Smoking Cessation," *New England Journal of Medicine*, 2015, *372* (22), 2108–2117. PMID: 25970009.

Higgins, Stephen T, Yukiko Washio, Alexa A Lopez, Sarah H Heil, Laura J Solomon, Mary Ellen Lynch, Jennifer D Hanson, Tara M Higgins, Joan M Skelly, Ryan Redner et al., "Examining two different schedules of financial incentives for smoking cessation among pregnant women," *Preventive Medicine*, 2014, *68*, 51–57.

References III

Hughes, John R., Josue Keely, and Shelly Naud, “Shape of the relapse curve and long-term abstinence among untreated smokers,” *Addiction*, 2004, *99* (1), 29–38.

Jin, Lawrence, Don Kenkel, Feng Liu, and Hua Wang, “Retrospective and Prospective Benefit-Cost Analyses of US Anti-Smoking Policies 1,” *Journal of Benefit-Cost Analysis*, 2015, *6* (1), 154–186.

Laibson, David, “Golden eggs and hyperbolic discounting,” *The Quarterly Journal of Economics*, 1997, *112* (2), 443–478.

Levy, Helen G., Edward C. Norton, and Jeffrey A. Smith, “Tobacco regulation and cost-benefit analysis: How should we value foregone consumer surplus?,” *American Journal of Health Economics*, 2018, *4* (1), 1–25.

Loewenstein, George, “Projection bias in medical decision making,” *Medical Decision Making*, 2005, *25* (1), 96–105.

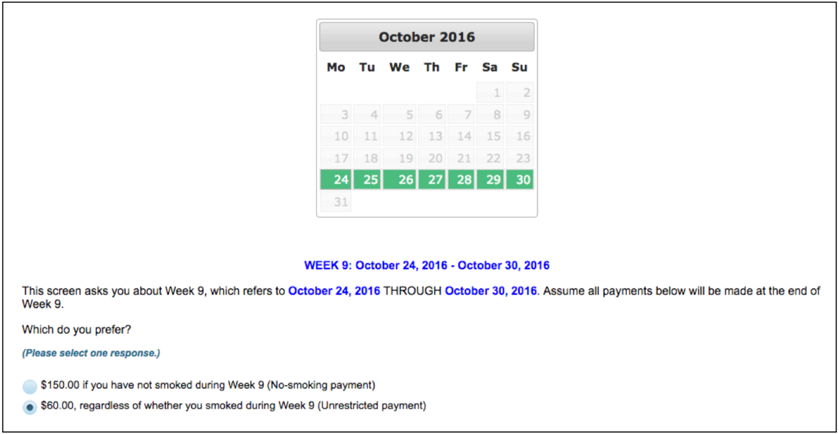
___ , Ted O’Donoghue, and Matthew Rabin, “Projection bias in predicting future utility,” *The Quarterly Journal of Economics*, 2003, *118* (4), 1209–1248.

O’Donoghue, Ted and Matthew Rabin, “Doing it now or later,” *American Economic Review*, 1999, *89* (1), 103–124.

Wertenbroch, Klaus, “Consumption self-control by rationing purchase quantities of virtue and vice,” *Marketing Science*, 1998, *17* (4), 317–337.

White, Justin S, Christopher Lowenstein, Nucharee Srivirojana, Aree Jampaklay, and William H Dow, “Incentive programmes for smoking cessation: Cluster randomized trial in workplaces in Thailand,” *BMJ*, 2020, *371*, m3797.

Sample elicitation choice



October 2016

Mo	Tu	We	Th	Fr	Sa	Su
					1	2
3	4	5	6	7	8	9
10	11	12	13	14	15	16
17	18	19	20	21	22	23
24	25	26	27	28	29	30
31						

WEEK 9: October 24, 2016 - October 30, 2016

This screen asks you about Week 9, which refers to **October 24, 2016** THROUGH **October 30, 2016**. Assume all payments below will be made at the end of Week 9.

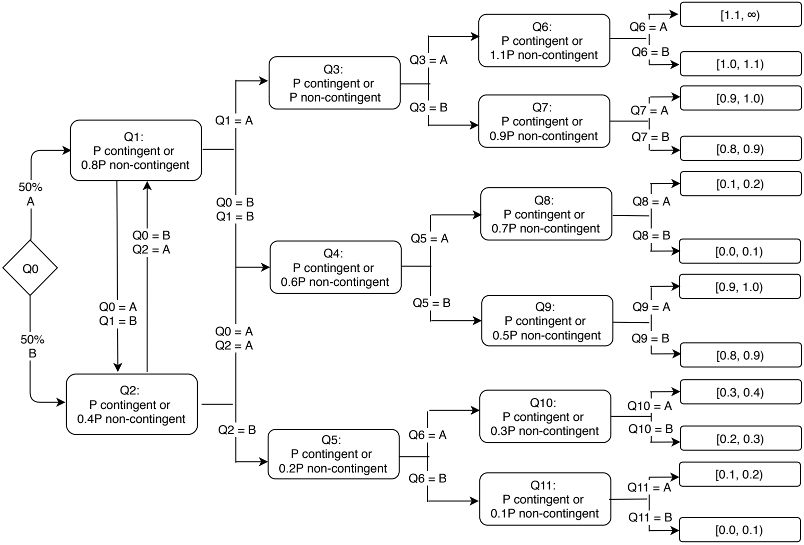
Which do you prefer?

(Please select one response.)

- $150.00 if you have not smoked during Week 9 (No-smoking payment)
- $60.00, regardless of whether you smoked during Week 9 (Unrestricted payment)

Note: This is an example of one of binary choices presented to subjects during the beliefs elicitation. In this case, p = \$150 and the non-contingent payment is 0.4p.

Belief elicitation staircase



▸ Back

Heterogeneity in over-optimism

	Demographics				Addiction-related				Health behaviors		
	Age	Male	Household income	Education	Cigarettes per day	Nicotine dependence	Quit plans	Present bias	Alcohol use	Sunscreen use	Overeats
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Behavior	-0.401***	-0.395***	-0.377***	-0.383***	-0.419***	-0.437***	-0.329***	-0.405***	-0.396***	-0.391***	-0.370***
	(0.021)	(0.018)	(0.020)	(0.017)	(0.024)	(0.020)	(0.021)	(0.019)	(0.015)	(0.022)	(0.024)
High group	-0.045	0.051	-0.020	0.024	-0.096***	-0.094***	0.176***	-0.046	-0.045	0.064**	0.049
	(0.031)	(0.034)	(0.032)	(0.036)	(0.031)	(0.031)	(0.031)	(0.033)	(0.066)	(0.032)	(0.032)
Behavior × High group	0.020	0.012	-0.029	-0.030	0.048	0.084***	-0.111***	0.041	0.079	0.002	-0.035
	(0.030)	(0.033)	(0.030)	(0.035)	(0.030)	(0.029)	(0.029)	(0.031)	(0.067)	(0.030)	(0.031)
Constant	0.536***	0.496***	0.523***	0.507***	0.572***	0.565***	0.415***	0.530***	0.516***	0.476***	0.485***
	(0.021)	(0.019)	(0.021)	(0.018)	(0.024)	(0.022)	(0.024)	(0.020)	(0.016)	(0.024)	(0.026)
R^2	0.25	0.26	0.25	0.25	0.26	0.26	0.28	0.25	0.25	0.26	0.25
Number of observations	7,185	7,185	7,161	7,185	7,185	7,185	7,185	7,185	7,185	7,185	7,185
Number of clusters	397	397	395	397	397	397	397	397	397	397	397

Note: The dep. var. is an indicator of weekly smoking abstinence. The data are stacked with observed behavior on top of predictions. “Behavior” equals 1 for observed abstinence and 0 for incentivized abstinence predictions. The “high” value of each dimension of heterogeneity, each measured at baseline, is listed at the top of each column. All models include individual random effects. All models include individual random effects. Age, household income, and alcohol use are dichotomized at the median. Education equals 1 if the person has at least some college or an associate’s degree. Cigarettes per day is split at ≥ 10. Nicotine dependence is split at Fagerström scores ≥ 4. Quit plans equals 1 if plans to quit within one year. Present bias, based on a hypothetical monetary choice task, equals 1 if prefers larger immediate payment and smaller later payment. Sunscreen use equals 1 if regularly uses sunscreen when outdoors. Overeats equals 1 if regularly eats an amount of food later regretted.

back

Structural estimation approach

Assume additively separable utility, with immediate displeasure from abstinence and delayed benefits:

$$U(abstain) = \beta_i \delta b + \gamma p - c_{it} \quad (1)$$

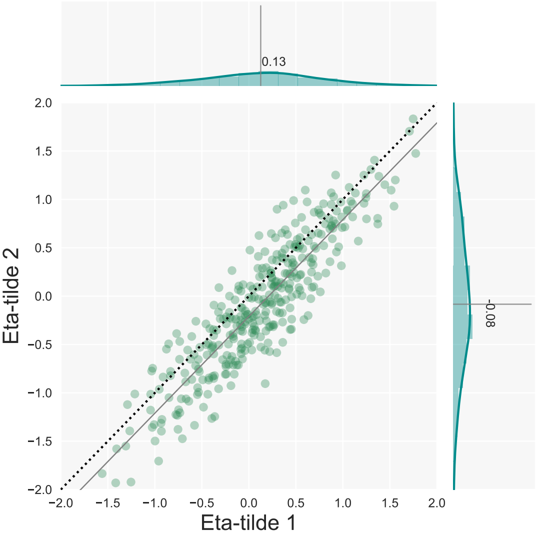
- Let δb represent value of being in abstinent state in full dynamic model
- Let cost c be decomposed into deterministic and stochastic components: $c_{it} = \mu_c + \varepsilon_{it}$, with ε_{it} standard logistic
- Month-2 treatment further reduces c by amount η, with beliefs pre- and post-treatment denoted by $\tilde{\eta}_1$ and $\tilde{\eta}_2$

Valuations of M3 incentives partially naïve if $\tilde{\beta} < 1$, with normal error

$$V(p|\theta) = \underbrace{pF(\tilde{\beta}\delta b + \gamma p - \mu_c)}_{\text{expected cash value}} + \underbrace{\gamma^{-1} \int_{\tilde{\beta}\delta b - \mu_c}^{\tilde{\beta}\delta b + \gamma p - \mu_c} (\delta b - \mu_c - \varepsilon) dF(\varepsilon)}_{\text{commitment value}} + \nu_{it} \quad (2)$$

- $\partial V / \partial p$ function of $(\tilde{\beta}\delta b - \mu_c)$ and $(1 - \tilde{\beta})\delta b$, invertible at large p under monotone hazard property of F

Beliefs about habit effect, $\tilde{\eta}_1$ and $\tilde{\eta}_2$



Habit effect $\eta = 0.56$ utils

1. $\alpha = 1 - \tilde{\eta}_1/\eta = 0.77$

   Fail to reject complete projection bias $(p = 0.45)$

2. $\eta - \tilde{\eta}_2 = 0.64\ (p = 0.04)$

   $\tilde{\eta}_1 - \tilde{\eta}_2 = 0.21\ (p = 0.08)$

   Not consistent with simple projection bias

3. Regression line: $\tilde{\eta}_2 = -0.21 + 1.00\tilde{\eta}_1$, $R^2 = 0.81$

Heterogeneity in structural parameters

Covariate	β	$\tilde{\beta}$	$\tilde{\eta}_1$	$\tilde{\eta}_2$
Constant	0.678^{*}	1.432^{***}	-1.091	0.036
	$[-0.076, 1.281]$	$[0.491, 2.923]$	$[-7.646, 3.210]$	$[-6.519, 4.340]$
Age (decades)	-0.002	-0.011^{***}	0.042^{***}	0.030^{**}
	$[-0.006, 0.001]$	$[-0.019, -0.005]$	$[0.013, 0.086]$	$[0.002, 0.076]$
Ln(Income)	0.017	0.005	0.017	-0.049
	$[-0.033, 0.073]$	$[-0.123, 0.111]$	$[-0.482, 0.585]$	$[-0.572, 0.480]$
Nicotine dependence	-0.000	-0.002	-0.127	-0.137
	$[-0.021, 0.025]$	$[-0.059, 0.064]$	$[-0.433, 0.152]$	$[-0.399, 0.127]$
Cigarettes	-0.006^{**}	-0.006	0.011	0.008
	$[-0.014, -0.000]$	$[-0.024, 0.009]$	$[-0.061, 0.093]$	$[-0.061, 0.093]$
Male	0.126^{***}	0.126	-0.011	0.405
	$[0.046, 0.200]$	$[-0.056, 0.298]$	$[-0.918, 0.802]$	$[-0.514, 1.178]$
Education	-0.004	0.035	-0.172	-0.348
	$[-0.047, 0.046]$	$[-0.094, 0.153]$	$[-0.651, 0.344]$	$[-0.777, 0.150]$
Quit plans	-0.029^{**}	-0.037^{*}	-0.110	-0.104
	$[-0.060, -0.004]$	$[-0.090, 0.000]$	$[-0.343, 0.190]$	$[-0.302, 0.210]$
Alcohol use	0.010	0.008	0.028	0.034
	$[-0.031, 0.024]$	$[-0.046, 0.024]$	$[-0.161, 0.219]$	$[-0.104, 0.238]$
Sunscreen use	0.080^{**}	-0.087	0.664^{*}	0.956^{**}
	$[0.002, 0.163]$	$[-0.272, 0.098]$	$[-0.123, 1.451]$	$[0.123, 1.723]$
Overeats	0.014	0.042	0.021	0.049
	$[-0.064, 0.099]$	$[-0.179, 0.188]$	$[-0.625, 1.025]$	$[-0.583, 0.987]$
Present bias (money)	-0.008	-0.054		
	$[-0.090, 0.062]$	$[-0.160, 0.037]$		

Additional tests of structural parameters

Test	Value	p-value
$b - \mu_c$	-0.100	0.916
$b - \mu_c + \eta$	0.455	0.156
$\bar{\tilde{\bar{\beta}}} - \bar{\beta}$	0.180	0.014
$\eta - \bar{\tilde{\bar{\eta}}}_1$	0.429	0.136
$\eta - \bar{\tilde{\bar{\eta}}}_2$	0.639	0.036
$\bar{\tilde{\bar{\eta}}}_1 - \bar{\tilde{\bar{\eta}}}_2$	0.210	0.084
$(b - \mu_c + \eta)/\gamma$	413.922	0.344

Comparing measures of naïveté

Use individual-level variation to explore if naïve present-biased beliefs are associated with projection-biased beliefs.

- Re-parameterize naïveté as linear combination of smallest and largest possible values:

  $$\tilde{\beta} = (1 - \omega)\beta + \omega(1)$$

  where $\omega = 0$ is full sophistication and $\omega = 1$ is fully naive beliefs.
- Regressing ω on projection bias α_{M1}, we find a strong positive association: $\omega = 0.46 + 0.29\alpha_{M1}$.