Tailoring Intertemporal Incentives: An Application to Polio Vaccination Drives in Pakistan

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Structural Models for Intertemporal Choice

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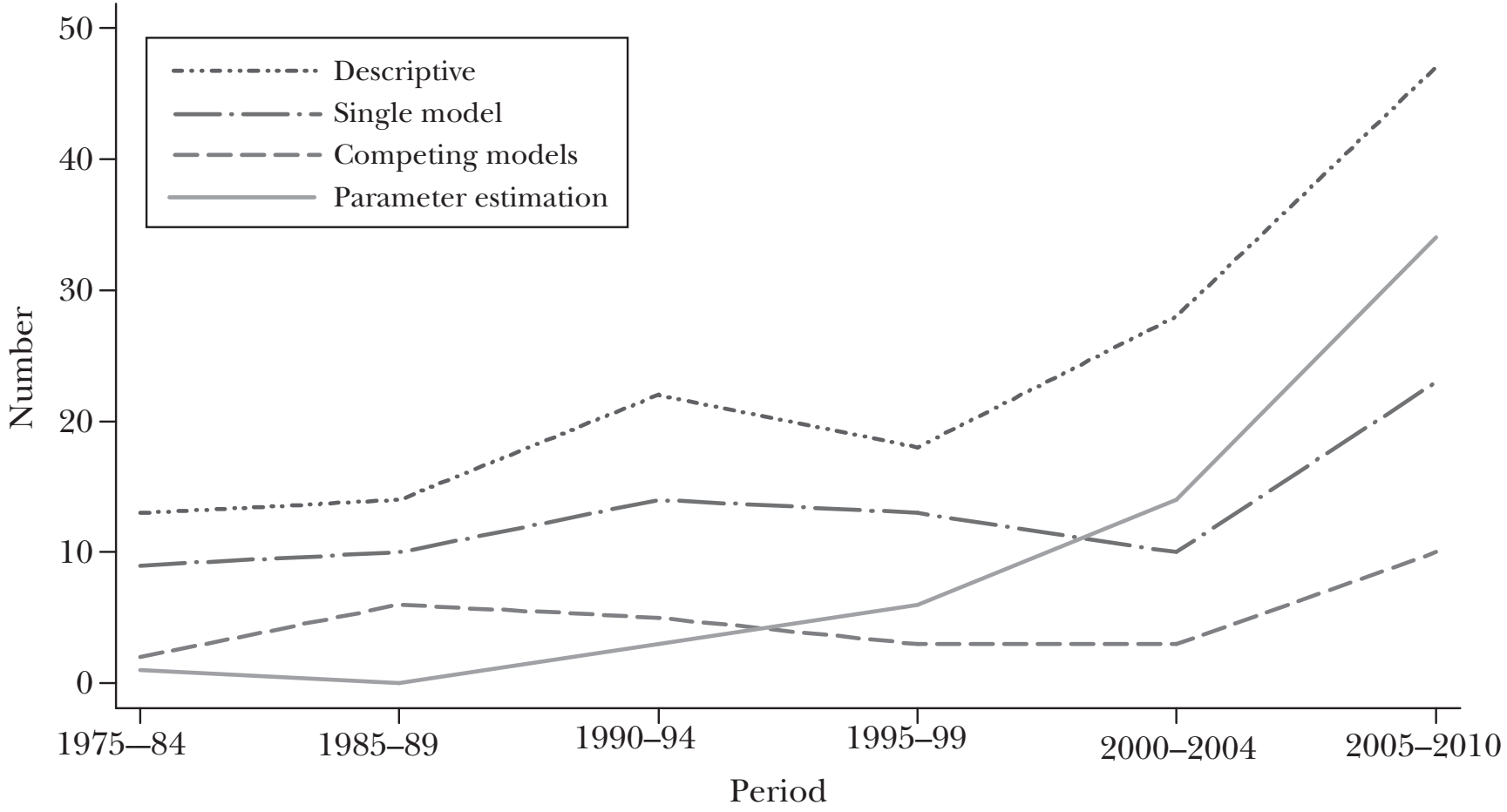
- Trend towards structural estimation not exclusive to the study of discounting.

From Card, Dellavigna, Malmendier (2011)

Laboratory Experiments by Theoretical Content



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     - These exercises are valuable, but the 'structural' aspect is unneccessary.

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  3. Directly test the predictions in a subsequent field experiment with the same subjects.
     - Implement smooth provision contract with half of subjects, examining benefits of tailored contracts.

Preview of Results

1. **Present Bias:** workers more likely to delay vaccinations when allocating immediately before the vaccination drive

2. **Preference-tailored Incentives:** Tailored contracts smooth intertemporal allocations:
   - Tailored subjects are 1/3 closer to the policy goal of smooth provision.

3. Benefits of tailoring may be greater when choices are immediate.

Outline

Background: Poliomyelitis

- Mainly affects children under five
- Attacks the nervous system and can cause paralysis within hours
- Children can be vaccinated by swallowing several drops of an oral vaccine
- 297 of 350 new polio cases occurred in Pakistan, constituting a "global public health emergency" according to the World Health Organization.

Department of Health Response to Polio

- The Department of Health organizes monthly polio drives
- Vaccinators spend at least two consecutive days traveling door-to-door to vaccinate children
- Vaccinators are given a neighborhood to cover and a target for vaccinations


پولیو کے دو قطرے
ہر بچہ ہر بار
پولیو سے بچاؤ کی مہم
سے بھرپور فائدہ اٹھائیں!

Status Quo Incentives

- Prior to our intervention, vaccinators self-reported achievement and were paid an unconditional wage of Rs. 100 a day
- In practice, vaccinators fall far short of their targets, but rarely report doing so
  - Consistent with a substantial literature on public sector absence (Chaudhury et al, 2006; Banerjee, Duflo, and Glennerster, 2008; Duflo, Hanna, Ryan, 2012; Callen et al, 2014)
- We implement smartphone monitoring.

Smartphone Monitoring

- Vaccinators carry a smartphone entering chalk-mark information and taking a picture of the chalk-mark on the compound wall.
- Every vaccination is time-stamped.
- Every 10th vaccination is also geo-stamped.
- Data filter directly to a dashboard.
- Permits observation of effort

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- Permits observation of effort
  - **Allows us to introduce pay-for-performance bonus contracts**

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Identifying Preferences I

- We offer vaccinators a fixed bonus ($10) for completing V vaccinations over a two-day drive.
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- **Timing:** Potential timing of selection is either in advance, $d = 0$, or immediate, $d = 1$.


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پولیو سروے
مقرر ہدف
پہلے دن: 133
دوسرے دن: 133
حتمی ہدف
مقرر ہدف

Identifying Preferences II

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  - e.g., quadratic costs: $\gamma = 2$
- Minimizing discounted costs subject to the intertemporal budget constraint of the experiment yields intertemporal Euler equation

$$\left(\frac{v_1}{v_2}\right)^{\gamma-1} \frac{1}{\beta^{\mathbf{1}_{d=1}}\delta} = \frac{1}{R}.$$

- Taking logs and rearranging yields

$$log\left(\frac{v_1}{v_2}\right) = \frac{log\delta}{\gamma-1} + \frac{log\beta}{\gamma-1}\mathbf{1}_{d=1} - \frac{1}{\gamma-1}logR.$$

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- Formulation gives insights for design.
  - Variation in R identifies γ.
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- Identical identification to that of Andreoni and Sprenger (2012) and Augenblick, Niederle and Sprenger (2015).
- Field experimental environment (1 allocation per worker) limits what can be achieved at the individual level.
  - Additional assumption $\gamma = 2$ for individual level exercise.
  - Implied discount factor is either $\beta\delta$ if $d = 1$ or δ if $d = 0$.

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Tailoring Contracts I

A policy-maker endowed with knowledge of worker time preferences controls the instrument R

The policy maker aims to solve:

$$max_R \; P(v_1^*(R), v_2^*(R))$$

$$s.t. \;\; (v_1^*(R), v_2^*(R)) = \quad argmin \; (v_1)^\gamma + \beta^{\mathbf{1}_{d=1}} \delta (v_2)^\gamma$$
$$s.t. \;\; v_t + Rv_2 = V.$$

- The solution to the policymaker's problem maximizes policy preferences, $P(v_1(R), v_2(R))$ subject to the constraint of the worker's offer curve, $(v_1(R), v_2(R)) = (v_1^*(R), v_2^*(R))$.

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- Denote the interest rate that solves this problem R^*

Tailoring Contracts: Leontief Preferences I

- Say a policymaker desires even provision of effort ($v_1 = v_2$)
- Leontief preferences: $P(v_1, v_2) = min[v_1, v_2]$
- The worker's intertemporal Euler equation $R^* \left(\frac{v_1}{v_2}\right)^{\gamma-1} = \beta^{\mathbf{1}_{d=1}}\delta$
- The model predicts that the interest rate R^* which gives smooth provision of effort is equal to the discount factor.
- $R^* = \beta^{\mathbf{1}_{d=1}}\delta$
- Without an estimate of the discount factor and a prediction for behavior, the policy-maker would have *no* idea how to tailor contracts.

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Experimental Overview

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- **Drive 2:** December, 8th and 9th (Incentive Tailoring Round)
  - Vaccinators inherit $d = 0/1$ assignment and are randomized (stratified) to either R^* or $R \in U[0.75, 1.5]$
  - Vaccinators with R^* outside of this interval are assigned to the boundary. We term them the 'boundary sample' and provide cuts of the data with and without.

Experimental Details

- Vaccinators in all conditions ($R \times d = 1$) invited to several central locations on Friday the week prior to the drive.
- Vaccinators are then trained in the use of the phone, including extensive practice.
- All conditions are made aware that they must make a decision prior to beginning the drive.
- The Advance Choice is prompted to make the allocation on Friday, after the training. The Immediate Choice is prompted to make the allocation at 7AM Monday morning.
  - A hotline number was made available to Immediate Choice workers.

Objectives: 1. Measure preferences
2. Test for dynamic inconsistency

Sample: 336

Notes: 82 vaccinators of the 336 could not select task allocations because of a problem with the app.

Sample Allocation:

	R=0.9	R=1	R=1.1	R=1.25
Advance Choice	42	42	42	42
Immediate Choice	42	42	42	42

Failed Drive 0: September 26 - 30, 2014

Objectives: 1. Measure preferences
2. Test for dynamic inconsistency

Sample: 349

Notes: Preferences are estimated for 338 of the 349 vaccinators.

Sample Allocation:

	R=0.9	R=1	R=1.1	R=1.25
Advance Choice	43	48	42	42
Immediate Choice	43	46	40	45

Drive 1: November 7 - 11, 2014

Objectives: 1. Test tailored contracts
2. Test tailoring by decision timing

Sample: Tailored (169)
Untailored (169)

Notes: All 338 vaccinators with a preference measurement from Drive 2 participated in Drive 3 and are assigned to either Tailored or Untailored.

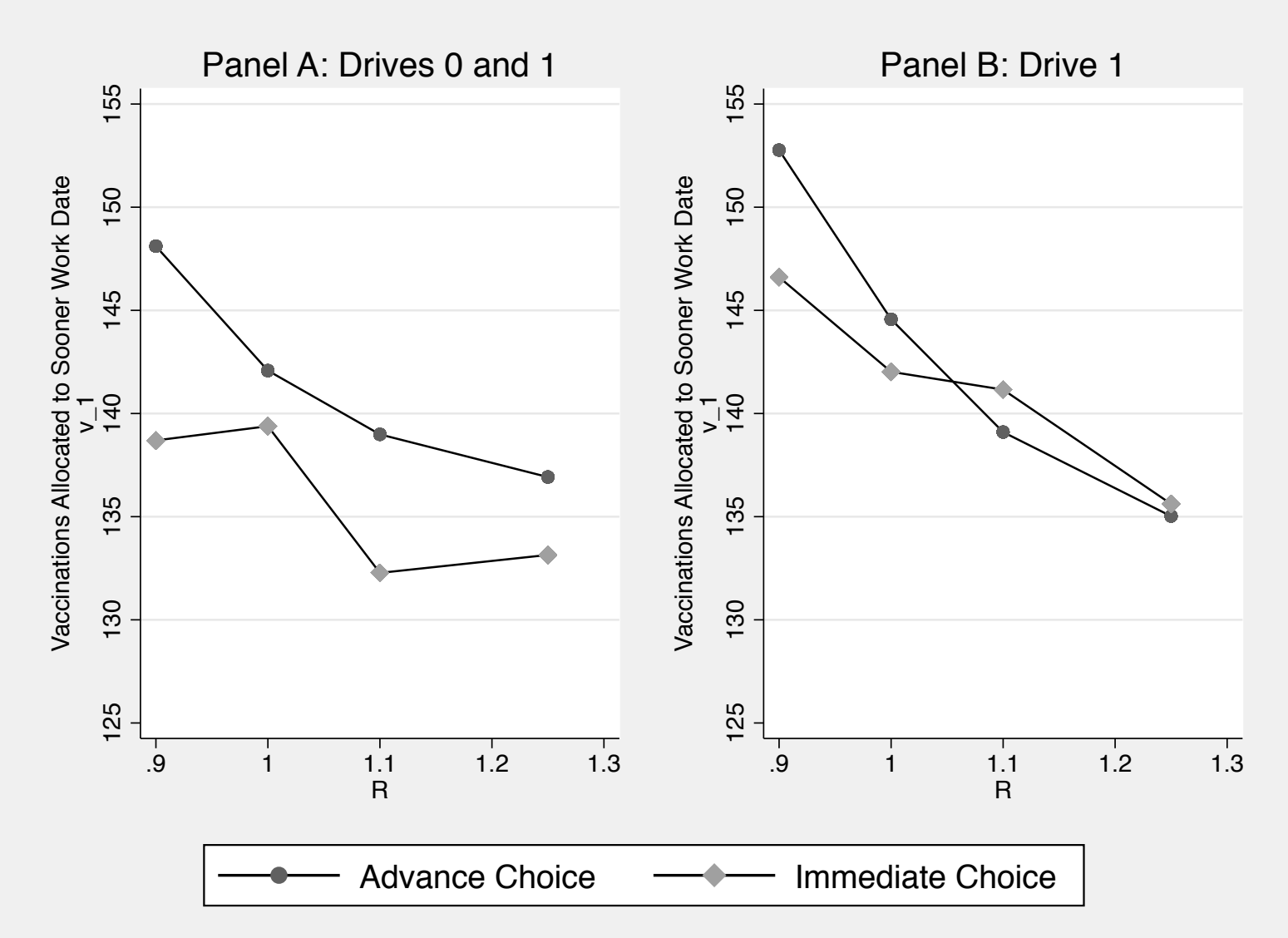
Sample Allocation:

	Tailored	Untailored
Advance Choice	85	89
Immediate Choice	84	80

Drive 2: December 5 - 9, 2014

Outline

Raw Data


Panel A: Drives 0 and 1
Panel B: Drive 1
Vaccinations Allocated to Sooner Work Date
v_1
125
130
135
140
145
150
155
.9
1
1.1
1.2
1.3
R
Advance Choice
Immediate Choice

Responsiveness to Experimental Variation

Dependent variable:	Tasks Allocated to the First Day of the Drive (v_1)							
	Drives 0 & 1 Combined				Drive 1			
	(1) OLS	(2) Median	(3) Median	(4) Median	(5) OLS	(6) Median	(7) Median	(8) Median
Immediate (d=1)	-5.62**	-2.00	-3.00***	-3.00**	-1.63	-2.00*	-3.00***	-2.14*
	(2.20)	(1.25)	(0.97)	(1.42)	(1.95)	(1.13)	(0.91)	(1.23)
Interest Rate (R)	-25.91***	-40.00***	-60.00***	-37.14***	-39.92***	-54.29***	-66.67***	-54.29***
	(7.78)	(4.83)	(3.82)	(5.42)	(7.42)	(4.38)	(3.66)	(4.68)
Constant	169.07	188.00	210.00	186.43	185.30	201.86	216.33	201.86
	(8.41)	(5.20)	(4.09)	(5.82)	(7.91)	(4.72)	(3.93)	(5.03)
Boundary Sample	Yes	Yes	No	Yes	Yes	Yes	No	Yes
Panel Sample	No	No	No	Yes	No	No	No	Yes
R-Squared	0.027				0.081			
Advance	141.54	150.00	150.00	150.00	142.87	146.50	148.00	146.50
# Observations	622	622	475	464	338	338	281	232

From Raw Data to Structural Estimates

$$log\left(\frac{v_1}{v_2}\right) = \frac{log\delta}{\gamma - 1} + \frac{log\beta}{\gamma - 1}\mathbf{1}_{d=1} - \frac{1}{\gamma - 1}logR.$$

- Links experimental variation to structural model of discounting.
- Assume an additive error term and estimable using conventional methods.
- Across specifications we put (severe) constraints on γ to force the function to be convex.

Structural Estimates

	Drives 0 & 1 Combined				Drive 1			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β	0.880	0.775	0.824	0.817	0.955	0.916	0.967	0.955
	(0.041)	(0.070)	(0.064)	(0.074)	(0.037)	(0.066)	(0.029)	(0.060)
δ	0.989	0.928	1.010	0.986	1.013	0.973	1.006	0.974
	(0.019)	(0.032)	(0.024)	(0.030)	(0.018)	(0.029)	(0.019)	(0.033)
a	-	-19.860	-15.415	-16.554	-	-19.827	-134.455	-20.045
	-	(0.492)	(0.408)	(0.445)	-	(1.189)	(8.736)	(0.190)
$\gamma = 1 + 2 \cdot \frac{1}{1+exp(a)}$	2	3	3	3	2	3	3	3
$ln(\sigma)$	-0.589	-0.623	-0.965	-0.767	-1.049	-1.122	-2.081	-1.453
	(0.089)	(0.094)	(0.146)	(0.124)	(0.150)	(0.176)	(0.039)	(0.089)
# Observations	622	622	475	464	338	338	281	232
Log-Likelihood	-516.137	-494.997	-215.567	-302.737	-125.092	-100.423	186.012	7.876
Boundary Sample	Yes	Yes	No	Yes	Yes	Yes	No	Yes
Panel Sample	No	No	No	Yes	No	No	No	Yes
$H_0 : \beta = 1$	$\chi^2(1) = 8.57$	$\chi^2(1) = 10.26$	$\chi^2(1) = 7.67$	$\chi^2(1) = 6.08$	$\chi^2(1) = 1.50$	$\chi^2(1) = 1.62$	$\chi^2(1) = 1.26$	$\chi^2(1) = 0.56$
	$(p < 0.01)$	$(p < 0.01)$	$(p < 0.01)$	$(p < 0.05)$	$(p = 0.22)$	$(p = 0.20)$	$(p = 0.26)$	$(p = 0.56)$

Structural Estimates

	Drives 0 & 1 Combined				Drive 1			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β	0.880	0.775	0.824	0.817	0.955	0.916	0.967	0.955
	(0.041)	(0.070)	(0.064)	(0.074)	(0.037)	(0.066)	(0.029)	(0.060)
δ	0.989	0.928	1.010	0.986	1.013	0.973	1.006	0.974
	(0.019)	(0.032)	(0.024)	(0.030)	(0.018)	(0.029)	(0.019)	(0.033)
a	-	-19.860	-15.415	-16.554	-	-19.827	-134.455	-20.045
	-	(0.492)	(0.408)	(0.445)	-	(1.189)	(8.736)	(0.190)
$\gamma = 1 + 2 \cdot \frac{1}{1+exp(a)}$	2	3	3	3	2	3	3	3
$ln(\sigma)$	-0.589	-0.623	-0.965	-0.767	-1.049	-1.122	-2.081	-1.453
	(0.089)	(0.094)	(0.146)	(0.124)	(0.150)	(0.176)	(0.039)	(0.089)
# Observations	622	622	475	464	338	338	281	232
Log-Likelihood	-516.137	-494.997	-215.567	-302.737	-125.092	-100.423	186.012	7.876
Boundary Sample	Yes	Yes	No	Yes	Yes	Yes	No	Yes
Panel Sample	No	No	No	Yes	No	No	No	Yes
$H_0 : \beta = 1$	$\chi^2(1) = 8.57$	$\chi^2(1) = 10.26$	$\chi^2(1) = 7.67$	$\chi^2(1) = 6.08$	$\chi^2(1) = 1.50$	$\chi^2(1) = 1.62$	$\chi^2(1) = 1.26$	$\chi^2(1) = 0.56$
	$(p < 0.01)$	$(p < 0.01)$	$(p < 0.01)$	$(p < 0.05)$	$(p = 0.22)$	$(p = 0.20)$	$(p = 0.26)$	$(p = 0.56)$

- Column (1) estimates compare favorably with Augenblick et al. (2015) for effort.
- Potential issue with specification as estimates consistently close to the box edge (still working on this).

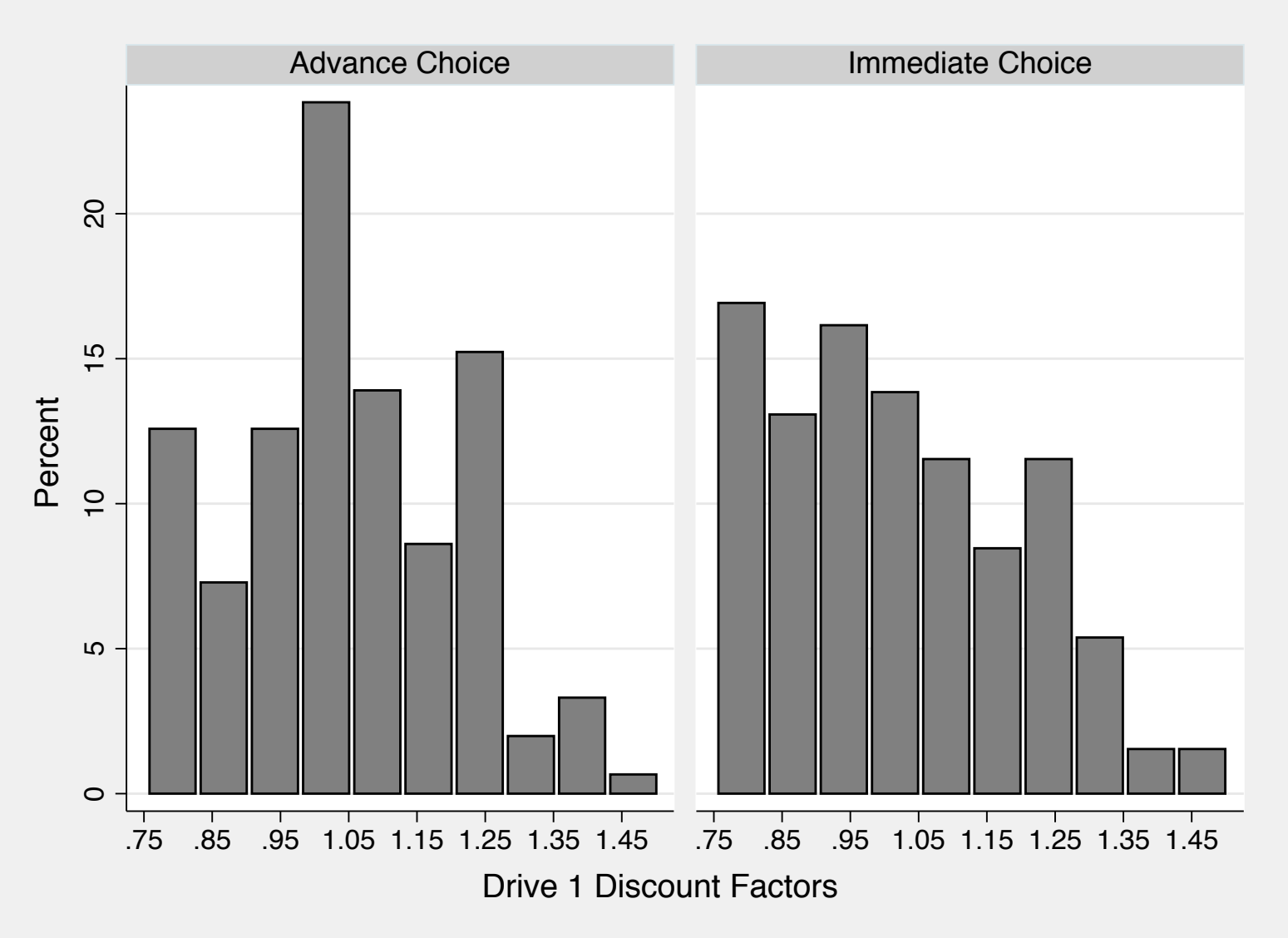
From Aggregate Estimates to Individual Discount Factors

- In addition to the assumptions of quasi-hyperbolically discounted stationary power costs, we assume that $\gamma = 2$ for all subjects.
- Under this assumption

$$\left(R\frac{v_1}{v_2}\right) = \beta^{\mathbf{1}_{d=1}}\delta$$

  the discount factor for each individual is directly calculable.
- This is discount factor used for tailoring.

Individual Discount Factors (excluding the boundary)



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- All structural exercises come with potentially implausible assumptions. A few are testable in our data
  1. Stationarity: Examine changes in distance walked or minutes taken per vaccination over time (no correlation with elicited preferences).
  2. Unobserved Costs: Examine long breaks (no correlation with elicited preferences)
  3. Homogeneity: Examine behavior when $R = 1$ under the assumption of no discounting (substantial heterogeneity remains).
  4. Cheap talk: On average 76% of target vaccinations are completed (no correlation between completion and preferences).

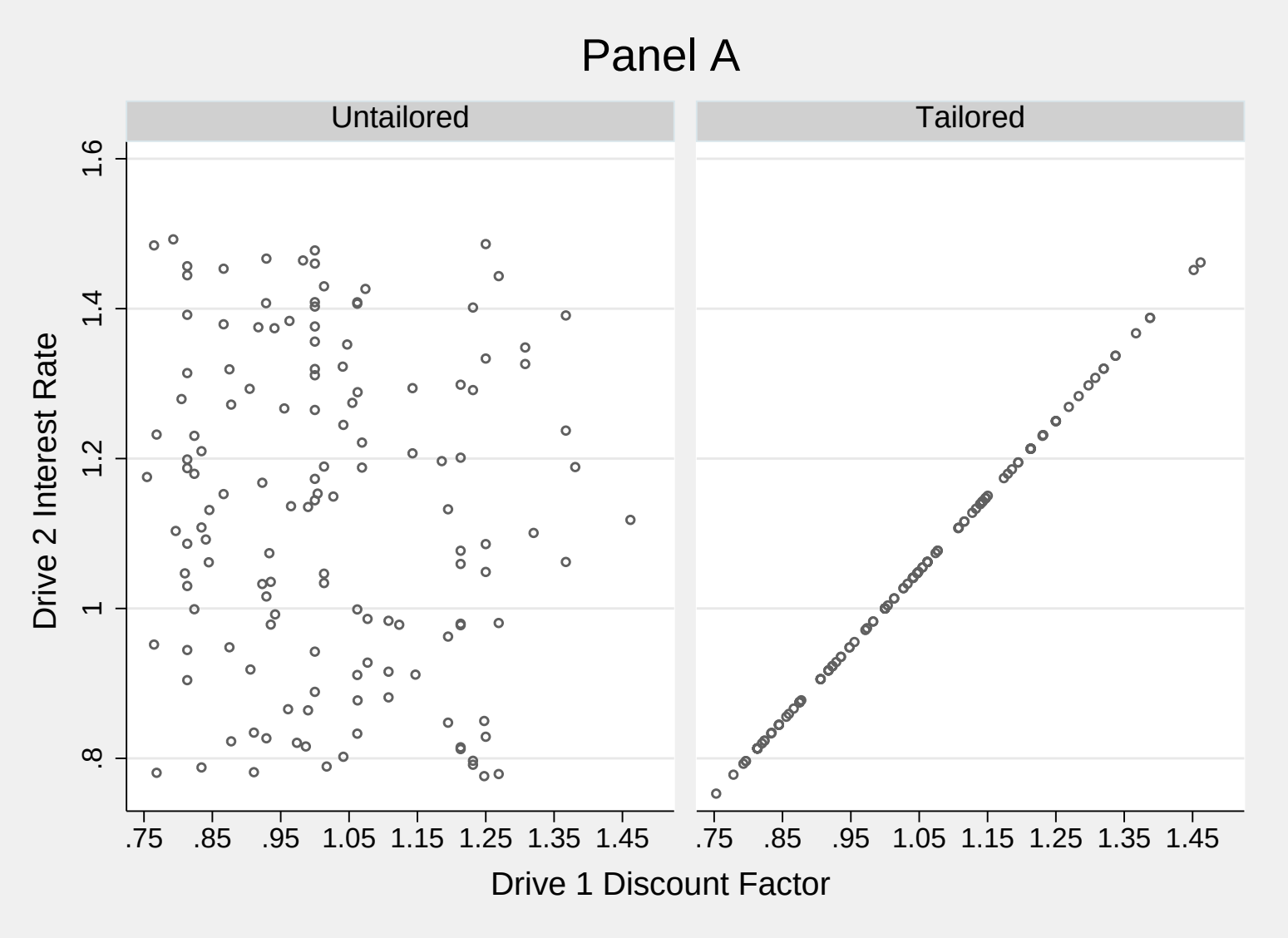
Individual Discount Factors and Tailoring

- Confounds to identification are a clear concern for structural exercises.
- Here, confounds work against finding predictive validity.

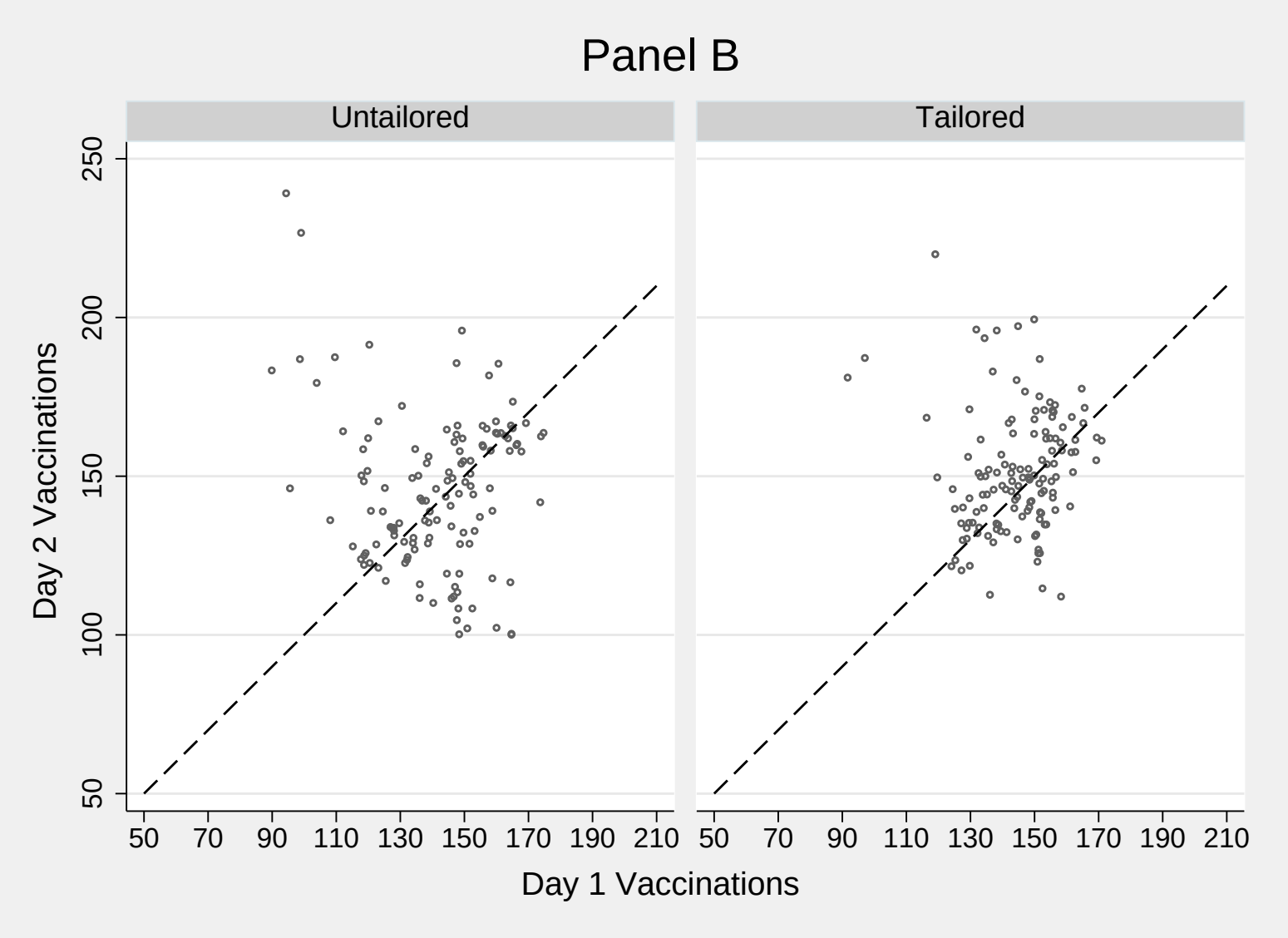
Proceed to Drive 2 Tailoring

Outline

Assignment of Intertemporal Contracts



Testing Tailored Incentives



Distance to Smooth Provision

Dependent variable:	$\left\lvert \frac{v_1}{v_2} - 1 \right\rvert$					
	(1)	(2)	(3)	(4)	(5)	(6)
Tailored (=1)	-0.544	-0.063***	-0.052**			
	(0.352)	(0.021)	(0.020)			
Immediate Choice (=1)						
Tailored x Immediate						
Constant	1.408	0.159***	0.025			
	(0.859)	(0.023)	(0.061)			
Stratum FEs	Yes	Yes	Yes	Yes	Yes	Yes
Exclude 99th and 1st Percentiles	No	Yes	Yes	No	Yes	Yes
Drive 2 R	No	No	Yes	No	No	Yes
Log-Likelihood	-625.629	69.504	72.117	-622.792	80.722	82.204
Mean in Untailored Contract	0.612	0.153	0.153	0.612	0.153	0.153
Mean in Untailored Advance				0.089	0.089	0.089
Mean in Untailored Immediate				0.701	0.169	0.169
# Vaccinators	280	267	267	280	267	267

Differential Effects by Timing

Dependent variable:	$\left\lvert \frac{v_1}{v_2} - 1 \right\rvert$					
	(1)	(2)	(3)	(4)	(5)	(6)
Tailored (=1)	-0.544	-0.063***	-0.052**	-0.086	-0.020	-0.015
	(0.352)	(0.021)	(0.020)	(0.142)	(0.021)	(0.021)
Immediate Choice (=1)				1.089*	0.130***	0.123***
				(0.616)	(0.037)	(0.036)
Tailored x Immediate				-0.953	-0.093**	-0.087**
				(0.643)	(0.042)	(0.042)
Constant	1.408	0.159***	0.025	0.809	0.090***	-0.003
	(0.859)	(0.023)	(0.061)	(0.534)	(0.028)	(0.060)
Stratum FEs	Yes	Yes	Yes	Yes	Yes	Yes
Exclude 99th and 1st Percentiles	No	Yes	Yes	No	Yes	Yes
Drive 2 R	No	No	Yes	No	No	Yes
Log-Likelihood	-625.629	69.504	72.117	-622.792	80.722	82.204
Mean in Untailored Contract	0.612	0.153	0.153	0.612	0.153	0.153
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Results to Here

- Elicited preferences show some hallmarks of present bias. Workers are more patient when choosing in Advance.
- Structural estimates have value for predicting out of sample behavior. Tailored contracts serve to reduce the distance from equal provision.
- Tailoring works particularly well in Immediate Choice.
- A set of natural robustness tests
  1. For the extent of present bias (relying on within subject variation).
  2. For the benefits of tailoring (relying on alternate dependent variables and treatment definitions).

Outline

Whither Present Bias?

- Growing set of studies identifies substantial present bias with non-monetary rewards.
- Using our Drive 1 data alone, evidence of present bias is somewhat thin.
- Note, however, that our Drive 1 data identifies present bias only from between subject variation, while most designs are within.
- Our failed Drive 0, and re-randomization allows us to examine within-subject variation for those who change timing across Drive 0 and 1.
- Also helps to address question of idiosyncratic shocks on day 1 of Drive 1 pushing towards present Bias.

Whither Present Bias?

	Complete Panel	No Change	Change	Imm. $\rightarrow$ Adv.	Adv. $\rightarrow$ Imm.
	(1)	(2)	(3)	(4)	(5)
β	0.817	0.836	0.798	0.700	0.886
	(0.074)	(0.113)	(0.097)	(0.178)	(0.073)
δ	0.986	0.965	1.007	1.038	0.983
	(0.030)	(0.043)	(0.040)	(0.047)	(0.061)
a	-16.554	-15.788	-16.609	-17.550	-21.683
	(0.445)	(0.814)	(0.549)	(0.970)	(0.835)
$\gamma = 1 + 2 \cdot \frac{1}{1+exp(a)}$	3	3	3	3	3
$ln(\sigma)$	-0.767	-0.862	-0.699	-0.389	-1.289
	(0.124)	(0.179)	(0.167)	(0.196)	(0.099)
# Observations	464	212	252	112	140
# Vaccinators	232	106	126	56	70
Log-Likelihood	-302.737	-118.101	-181.540	-115.316	-18.227
$H_0 : \beta = 1$	$\chi^2(1) = 6.076$	$\chi^2(1) = 2.081$	$\chi^2(1) = 4.348$	$\chi^2(1) = 2.858$	$\chi^2(1) = 2.444$
	$(p < 0.01)$	$(p = 0.14)$	$(p < 0.05)$	$(p < 0.10)$	$(p = 0.12)$

Alternate Dependent Variables

Panel A: Dependent variable $\frac{|v_1 - v_2|}{\sqrt{2}}$

	(1)	(2)	(3)	(4)	(5)	(6)
Tailored (=1)	-2.338	-4.773**	-4.821**	-2.723	-1.813	-2.027
	(4.867)	(2.107)	(2.244)	(3.087)	(2.399)	(2.461)
Immediate Choice				22.566***	10.883***	11.158***
				(6.288)	(3.498)	(3.608)
Tailored x Immediate				1.759	-6.323	-6.551
				(10.221)	(4.335)	(4.377)
Constant	31.309***	16.390***	16.978**	18.441***	10.673***	14.464**
	(7.380)	(2.356)	(7.229)	(6.564)	(2.901)	(7.007)

Panel E: Dependent variable $|v_1 - \frac{300}{1+R}| > 25$

	(1)	(2)	(3)	(4)	(5)	(6)
Tailored (=1)	-0.454**	-0.654***	-0.578***	-0.282	-0.282	-0.235
	(0.191)	(0.221)	(0.216)	(0.317)	(0.314)	(0.309)
Immediate Choice				0.920***	0.720**	0.697**
				(0.272)	(0.283)	(0.286)
Tailored x Immediate				-0.275	-0.676	-0.653
				(0.408)	(0.462)	(0.460)
Constant	-0.639***	-0.887***	-1.568**	-1.231***	-1.312***	-1.812***
	(0.206)	(0.239)	(0.637)	(0.304)	(0.335)	(0.665)
Log-Likelihood	-110.271	-83.129	-82.513	-101.934	-79.678	-79.351
# Vaccinators	280	267	267	280	267	267
Stratum FEs	Yes	Yes	Yes	Yes	Yes	Yes
Exclude 99th and 1st Percentiles	No	Yes	Yes	No	Yes	Yes
Drive 2 R	No	No	Yes	No	No	Yes

Alternate Treatment Measures

Panel A: Tailoring Intensity

	(1)	(2)	(3)	(4)	(5)	(6)
Tailor Intensity	2.745	0.175**	0.122*	0.198	0.133	0.098
	(2.141)	(0.068)	(0.067)	(0.373)	(0.085)	(0.081)
Immediate Choice				-0.017	0.074***	0.072***
				(0.321)	(0.024)	(0.024)
Tailor Intensity x Immediate				4.681	0.073	0.061
				(3.842)	(0.138)	(0.135)
Constant	0.720*	0.101***	-0.007	0.678	0.062***	-0.017
	(0.435)	(0.018)	(0.060)	(0.452)	(0.021)	(0.060)
# Vaccinators	280	267	267	280	267	267

Panel B: Tailoring Intensity and Boundary Sample

	(1)	(2)	(3)	(4)	(5)	(6)
Tailor Intensity	1.318	0.159**	0.133**	-0.007	0.057	0.029
	(1.051)	(0.070)	(0.066)	(0.244)	(0.063)	(0.058)
Immediate Choice				0.142	0.070***	0.068**
				(0.215)	(0.027)	(0.026)
Tailor Intensity x Immediate				2.185	0.153	0.159
				(1.888)	(0.121)	(0.116)
Constant	0.651*	0.148***	0.045	0.565*	0.113***	0.015
	(0.348)	(0.026)	(0.067)	(0.340)	(0.026)	(0.065)
# Vaccinators	337	320	320	337	320	320
Stratum FEs	Yes	Yes	Yes	Yes	Yes	Yes
Exclude 99th and 1st Percentiles	No	Yes	Yes	No	Yes	Yes
Drive 2 R	No	No	Yes	No	No	Yes

Outline

Conclusion

- In the domain of time preference, where the structural machinery is substantial, little use is made thereof.
- We attempt to elicit time preferences, structurally estimate discounting parameters, and assess out-of-sample predictive ability.
- Our context and our out-of-sample environment are clearly policy relevant. Intertemporal government service provision where the policy-maker wishes to ensure smooth provision through time.

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- Three findings:
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  3. Tailoring may work better when choice is immediate.
- Exercise suggests that investment in structural estimation may be warranted.
- Potential for simple elicitation devices to yield concrete tailoring benefits for policymakers (or firms).

Thank you!

Partners and Collaborators

- Rashid Langrial, Commissioner, Lahore Division
- Punjab Department of Health
- International Growth Center (IGC)
- Muhammad Usman, District Coordinating Officer, Lahore
- Zulfiqar Ali, Executive District Officer Health