Time inconsistency and non-stationary instantaneous utility: empirical evidence from rural Malawi

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Outline

Empirical evidence of time inconsistency

- Which option do you prefer?
  A) £100 today
  B) £110 next week
- Which option do you prefer?
  C) £100 one year from now
  D) £110 one year and a week from now

Most people choose $A \succ B$ and $D \succ C$, providing evidence of **time inconsistency**: a person's relative preference for well-being at an earlier date over a later date changes according to when she is asked.

This behaviour has been consistently detected in humans, rats and pigeons. (Ainslie, 1974)

- Time inconsistency is a puzzling result as it is in contrast with the predictions of the **discounted utility framework**[1] (DU).
- Most of the DU assumptions are very restricting and have been deeply falsified by empirical evidence.
- Nevertheless, the model is still very popular because of its simplicity, elegance and tractability.

[1] Samuelson, Paul A. "A note on measurement of utility." The review of economic studies 4.2 (1937): 155-161.

DU framework in a nutshell

- Consider an economy that lasts $t = 1, \ldots, T$ periods.
- The decision maker has preferences over consumption profiles $c_t = (c_{t,t}, c_{t+1,t}, \ldots, c_{T,t})$, where $c_{t,s}$ denotes the level of consumption in period t from period s' perspective, with $s, t \in \mathcal{T} = \{1, \ldots, T\}$.
- The agent has an initial endowment s_0.
- Postponing consumption to the next period gives a net return $r > 0$.

DU framework in a nutshell

- Under completeness, transitivity and continuity the preferences over consumption profiles can be represented by an intertemporal utility function:

$$U^t(c_t, \dots, c_T) = \sum_{k=0}^{T-t} \delta^k u(c_{t+k})$$

- At each period t, the player chooses the optimal consumption profile $c_t^* = (c_{t,t}^*, c_{t+1,t}^*, \dots, c_{T,t}^*)$ by maximising her intertemporal utility function.
- The initial optimal consumption plan is optimal for all the subsequent periods: $c_{t,s}^* = c_{t,t}^* \forall s, t \in \mathcal{T}$.

Intertemporal choice and DU model

DU model is based on the following set of assumptions:

1. Integration of new alternatives with existing plans
2. Utility independence
3. Consumption independence
4. Stationary instantaneous utility
5. Independence of discounting from consumption
6. Constant discounting and time consistency
7. Diminishing marginal utility and positive time preference

Intertemporal choice and DU model

Almost each assumption is usually violated by the empirical evidence:

1. Limited ability of intertemporal reoptimization
2. Habit formation
3. Preference for spread
4. State-dependent preferences
5. Labeled discount factors
6. Time inconsistency and present bias

- Literature usually explains time inconsistency by relaxing the DU assumption of constant discounting in favour of hyperbolic discounting: a person has a declining rate of time preferences.
- This idea has both sociological and psychological justifications.
- The most famous model of hyperbolic discounting is the (β, δ)[2].
- However, it is unclear why the psychological motives should modify the discount factor rather then the utility function.
- The same phenomenon (and maybe more) can be explained by relaxing the assumption of stationary instantaneous utility.

[2] Laibson, David. "Self-control and saving." Massachusetts Institute of Technology mimeo (1994).

Advantages of the setting

Relaxing the assumption of stationary instantaneous utility rather than constant discounting provides several advantages:

1. Economic interpretation of fluctuations of the instantaneous utility is more intuitive.
2. Future-biased behavior becomes plausible.
3. Existence of a symmetric application to state-dependent preferences rather than time-dependent.

Alternatives to the DU framework

- **Standard DU model**:

$$U^t(c_t, \ldots, c_T) = \sum_{k=0}^{T-t} \delta^k u(c_{t+k})$$

- (β, δ)-**preferences**:

$$U^t(c_t, \ldots, c_T) = u(c_t) + \beta \sum_{k=t+1}^{T} \delta^k u(c_k)$$

- **Dynamic utility**:

$$U^t(c_t, \ldots, c_T) = \sum_{k=0}^{T-t} \delta^k u_t(c_{t+k})$$

Dynamic preferences' update

- My model provides an alternative set-up to deal with time inconsistency by relaxing the assumption of stationary instantaneous utility.
- The novelty consists in the introduction of **law of motion** for the utility function relying on this semi-parametric assumption:

$$U^t(c_t, \dots, c_T) = \sum_{k=0}^{T-t} \delta^k [u(c_{t+k})]^{\beta_t}$$

- The semi-parametric approach allows to understand the main intuition of the phenomenon with a minimal divergence from the DU framework.
- All the other assumptions of the DU framework are retained.

The concavifying parameter

- β_t is an **unexpected** shock to the player's elasticity of intertemporal substitution at time t.
- The agent is **naive**: at any period, $E_t(\beta_t) = 1$.
- We remain agnostic on the reasons why β_t arises.
- β_t has the following law of motion:

$$\beta_t = \begin{cases} 1 & \text{if } t = 1 \\ x_t & \text{if } t > 1 \end{cases}$$

$$x_t = \begin{cases} \beta_t^H \geq 1 & \text{w.p. } \theta \\ 0 < \beta_t^L < 1 & \text{w.p. } (1-\theta) \end{cases}$$

with $\theta \in [0, 1]$. Draws are independent over time.

Characterisation of the β-transformation

Let us consider the following items:

- a consumption set $C \subseteq \mathbb{R}_+$
- a C^2 utility function $u : C \to \mathbb{R}_+$, with $u'(c) \geq 0$ and $u''(c) \leq 0$
- a real number $\beta > 0$
- a function $v : C \times \mathbb{R} \to \mathbb{R} : v(c, \beta) = u(c)^\beta$.

Some restrictions on β must be imposed so that $v(c)$ still represents convex preferences. In particular, the following is true:

Proposition 1

The maximum shock each agent can tolerate while retaining convex preferences is measured by the **resilience parameter** $\tilde{\beta} = 1 - \frac{u''(c) \cdot u(c)}{u'(c)^2}$.

Proof.

Consider $v(c) = u(c)^{\beta}$. This function represents convex preferences iff $v''(c) \leq 0$:

$$v''(c) = \beta u(c)^{(\beta-1)} \cdot \left[u''(c) + (\beta - 1)\frac{u'(c)^2}{u(c)} \right] \leq 0$$

$$\Rightarrow \beta \in (0, \tilde{\beta})$$

where $\tilde{\beta} = 1 - \frac{u''(c) \cdot u(c)}{u'(c)^2}$. □

The resilience parameter

- $\tilde{\beta}$ depends on both the value of c and the shape of u. People can have different values of $\tilde{\beta}$ because either their preferences are represented by different utility functions or because they have the same utility function but made different choices.
- the larger the interval $(1, \tilde{\beta})$, the more likely the individual is to retain convex preferences after a big shock. When making a choice of c under u, the decision maker implicitly determines the maximum shock she can tolerate while keeping standard behaviour.
- Since $\tilde{\beta}$ depends on c, $\tilde{\beta}$ will generally be time-dependent in the intertemporal choice framework.

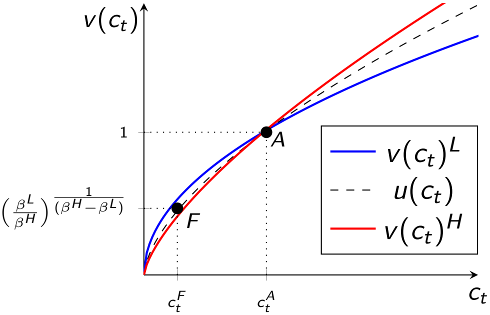
The resilience parameter

Focus on the second term of $\tilde{\beta}$:

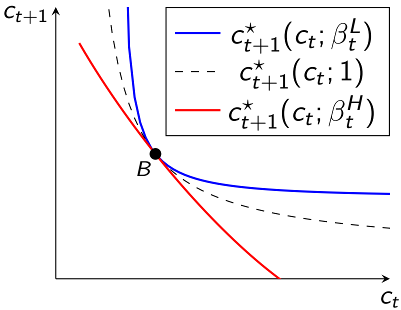
$$\frac{u''(c)\cdot u(c)}{u'(c)^2} = \frac{u''(c)}{u'(c)} \cdot \frac{u(c)}{u'(c)}$$

- $\frac{u''(c)}{u'(c)} = \frac{d\log(u'(c))}{dc}$: percentage change in marginal utility
- $\frac{u'(c)}{u(c)} = \frac{d\log(u(c))}{dc}$: percentage change in level utility

The term measures the **elasticity of the marginal utility with respect to the level utility**. So, it evaluates how much the power transformation can bend the utility function before making it linear.

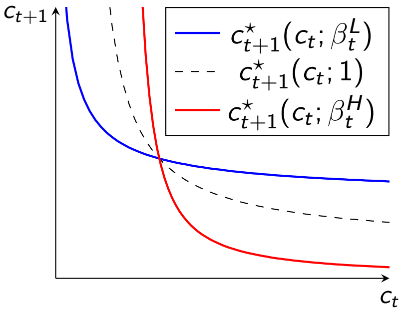


- The value functions are both increasing, and they cross at the point c_A s.t. $u(c_t^A) = 1$
- v^H is steeper than v^L as long as $u(c_t) \geq \left(\frac{\beta^L}{\beta^H}\right)^{\frac{1}{(\beta^H-\beta^L)}}$
- v^L is unambiguously more concave than v^H, which becomes convex if $\beta^H \geq \tilde{\beta}$



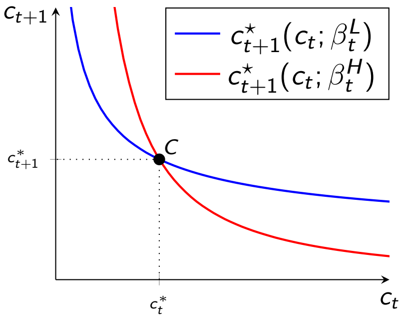
- If $\beta_t < 1$ ($\beta_t > 1$), the indifference curve becomes unambiguously **more** (less) **eccentric**.
- As the EIS increases (decreases), the agent requires weakly less (more) future consumption — given the same level of current consumption — in order to stick on the same utility level.
- If $\beta_t \geq \tilde{\beta}_t$, the indifference curve becomes concave.

The tilting effect



- If $\beta_t < 1$ ($\beta_t > 1$), the indifference curve is **tilted to the left** (right).
- The net effect of the change in EIS depends on the level of current consumption.
- If $\beta_t < 1$ ($\beta_t > 1$), the change in future consumption required to stay on the same utility level is higher (lower) for small (high) amounts of current consumption.

Single-crossing condition



Single-crossing condition for time-dependent indifference curves:

$$\left| \frac{\partial c_{t+1}}{\partial c_t}\bigg|_{\beta_t \geq 1} \right| > \left| \frac{\partial c_{t+1}}{\partial c_t}\bigg|_{\beta_t < 1} \right|$$

with $\lim_{c_t \to 0} \left[c^\star_{t+1}(c_t;\beta^H_t) - c^\star_{t+1}(c_t;\beta^L_t) \right] \geq 0$

Dynamic optimality conditions

At each period t, optimality requires:

$$\left[\frac{u(c_{t+k})}{u(c_t)}\right]^{(\beta_t - 1)} \cdot \frac{u'(c_{t+k})}{u'(c_t)} = [\delta(1+r)]^k \quad (1)$$

- The marginal rate of substitution at time t of consumption in any two periods depends on the realisation of β_t.
- It might be optimal to revise the consumption plan at each period.
- Crucially, this could lead to present-biased behaviour as well as feature-biased.

Evolution of the EIS

- We expect the β-transformation to modify the elasticity of intertemporal substitution (EIS), which we denote as $\gamma(c_t; \beta_t)$.
- $\gamma(c_1; 1) = \gamma_1$ denotes the EIS at $t = 1$, *before* any β-transformation.
- $\gamma(c_t; \beta_t) = \gamma_t$ with $t \neq 1$ denotes the EIS of the instantaneous utility at time t *after* the transformation.
- Our goal is to study the behaviour of γ_t assuming $\beta_t \in (0, \tilde{\beta}_t)$.

Evolution of the EIS

- The abstract definition of elasticity of intertemporal substitution[3] is:

$$\gamma_v = -\frac{v'(c)}{c \cdot v''(c)} \tag{2}$$

where $v'(c)$ and $v''(c)$ denote the first and the second order derivative of v evaluated at point c, respectively.

- Since $v(c, \beta) = u(c)^\beta$, (2) is equivalent to:

$$\gamma_v = -\frac{u'(c)}{c\left[u''(c) + (\beta - 1) \cdot \frac{u'(c)^2}{u(c)}\right]} \tag{3}$$

- Notice that $\beta < \tilde{\beta} \Rightarrow \gamma_v \geq 0$ and $\lim_{\beta \to \tilde{\beta}} \gamma_v = \infty$.

[3] Hall, Robert E. "Intertemporal Substitution in Consumption." Journal of Political Economy 96, no. 2 (1988): 339–57.

Evolution of the EIS

Proposition 2

Assume $v(c) = u(c)^\beta$ *and* $\beta \in (0, \hat{\beta})$. *Then* $\gamma(c, \beta)$ *is increasing in* β.

Proof.

We want to show that for any pair (β_1, β_2) and for any $c \in C$, $\beta_1 < \beta_2 \Rightarrow \gamma(c, \beta_1) \leq \gamma(c, \beta_2)$. Let us assume by contradiction this is not the case: $\exists c \in C$ and a pair (β_1, β_2) with $\beta_1 < \beta_2$ such that $\gamma(c, \beta_1) > \gamma(c, \beta_2)$. From Equation (3), this means:

$$-\frac{u'(c)}{c\left[u''(c) + (\beta_1 - 1) \cdot \frac{u'(c)^2}{u(c)}\right]} > -\frac{u'(c)}{c\left[u''(c) + (\beta_2 - 1) \cdot \frac{u'(c)^2}{u(c)}\right]} \tag{4}$$

Using the fact that $\beta_1 \in (0, \hat{\beta})$ and $\beta_2 \in (0, \hat{\beta})$, Equation (4) simplifies to $\beta_1 > \beta_2$, contradicting our initial statement. □

Application to CRRA

Assume $u(c) = \frac{c^{(1-\sigma)}}{1-\sigma}$, with $\sigma \in (0, 1)$.

Then, the following results:

1. $\tilde{\beta}_t = \tilde{\beta} = \frac{1}{1-\sigma}$
2. $\gamma_t = (1 + \sigma\beta_t - \beta_t)$
3. $u(c_t)^{\beta_t} = \left[\frac{c^{(1-\sigma)}}{1-\sigma}\right]^{\beta_t} = \frac{\beta_t}{(1-\sigma)^{(\beta_t - 1)}} \frac{c_t^{(1-\gamma_t)}}{1-\gamma_t}$

Summary

1. Non-stationary instantaneous utility leads to different optimal solutions with respect to the theoretical benchmark.
2. Optimality usually requires a repeated revision of the consumption plan.
3. At each period t, the decision maker implicitely defines her resilience parameter, which is only partially determined by her intrinsic baseline preferences.
4. The net effect of a shock to the EIS can be split in a bending effect and a tilting effect.
5. According to the realisation of the shock, the revised optimal plan could either increase or decrease current consumption, explaining both present-biased and future-biased behavior.

Empirical results

Estimated parameters

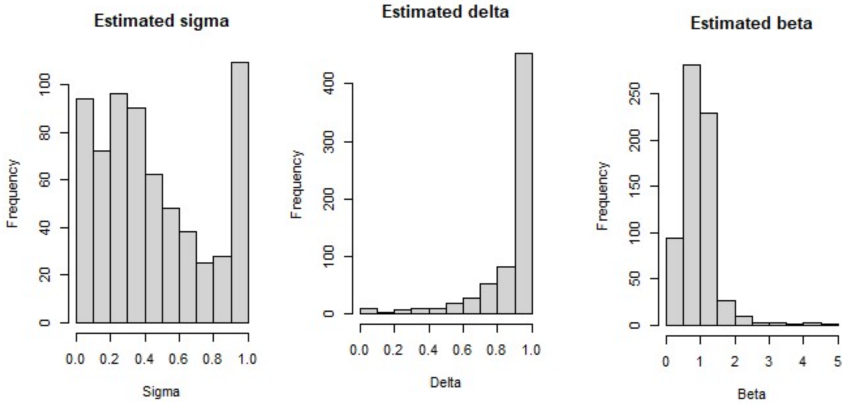
- **Probability to get an high shock:** $\hat{\theta} = 0.5$
- **Discount factor:** $\hat{\delta} = 0.89$
- **EIS reciprocal:** $\hat{\sigma} = 0.45$
- **Average beta:** $\hat{\beta} = 1.34$
- **Average high beta:** $\hat{\beta}^H = 2.04$
- **Average low beta:** $\hat{\beta}^L = 0.66$

- Time-inconsistent plans: 93%
- Present-biased revisions: 30.5% [4]
- Future-biased revisions: 36.7% [5]

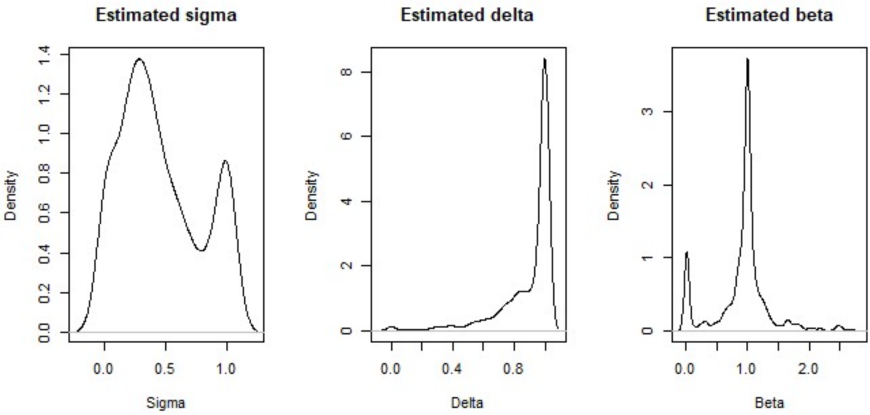
[4] At least 3 present-biased revisions out of 5.

[5] At least 3 future-biased revisions out of 5.

Estimated parameters



Estimated parameters



Correlations

	δ	$\frac{1}{\sigma}$	β
δ	1	0.162	0.003
$\frac{1}{\sigma}$	0.162	1	-0.034
β	0.003	-0.034	1

Table: Correlation matrix

- The analysis reveals a slight positive correlation between the discount rate and the elasticity of intertemporal substitution.
- The result is in line with economic intuition: the higher is the elasticity of intertemporal substitution, the higher the weight the agent assigns to future periods.
- There is no empirical evidence of meaningful correlation between the other parameters of interests.

Correlations

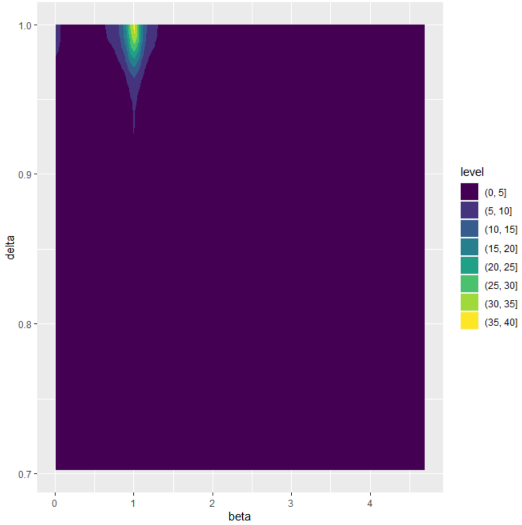


Figure: Contours of kernel density estimation of (β, δ)

Correlations

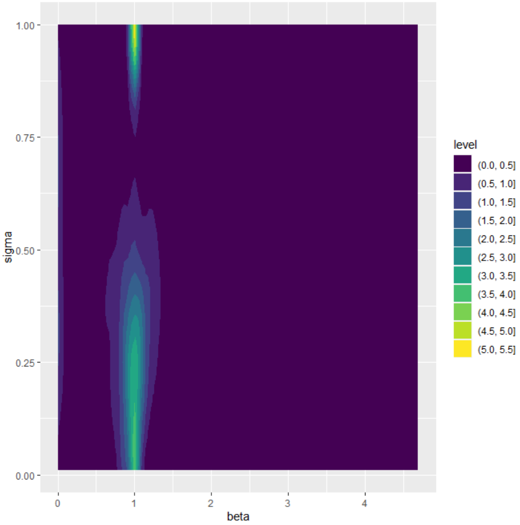


Figure: Contours of kernel density estimation of (β, σ)

Correlations

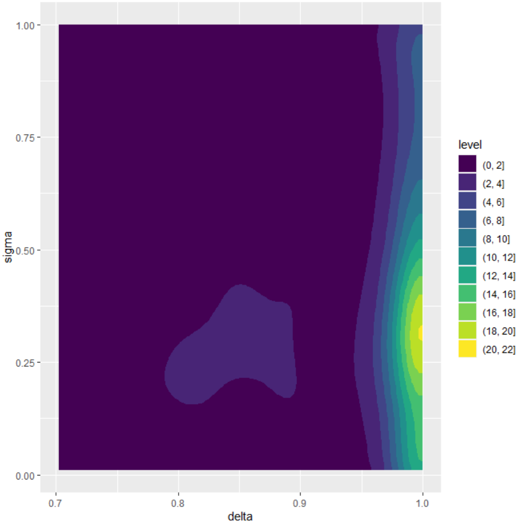
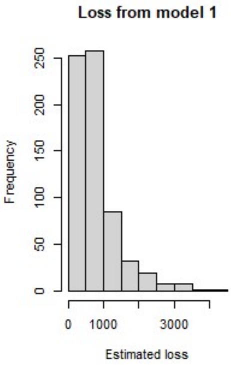
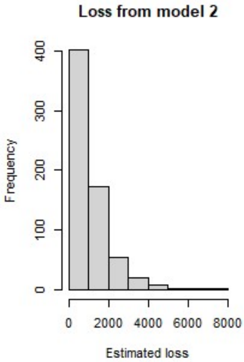


Figure: Contours of kernel density estimation of (δ, σ)

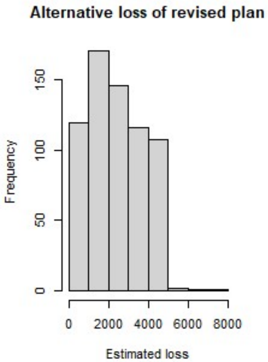
Loss functions



(a) Loss of model 1 for period 1

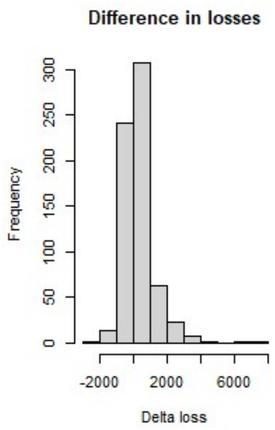


(b) Loss of model 2 for period 2

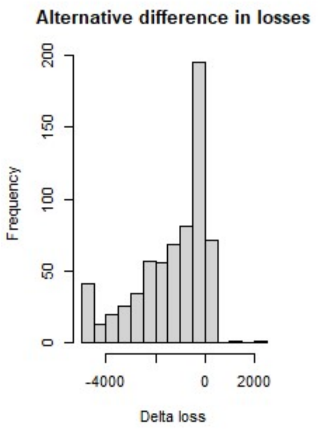


(c) Loss of model 1 for period 2

Loss functions



(a) Difference in loss between model 2 for period 2 and model 1 for period 1



(b) Difference in loss between model 2 for period 2 and model 1 for period 2

Model validation

```
Call:
lm(formula = loss.1 ~ male + younger + older + +no_school + some_primary +
    primary + wealth_bline + r + wrdrecal_1 + ravens + finlit_total +
    deathinfam + delta_income + delta_hh_tot_exp, data = mydataset)

Residuals:
   Min     1Q Median     3Q    Max
-936.2 -397.5 -104.3  203.8 3206.8

Coefficients:
                  Estimate Std. Error t value    Pr(>|t|)
(Intercept)      853.24403  159.26276   5.357 0.000000117 ***
male             -49.77443   55.11703  -0.903       0.367
younger           11.64881   61.42851   0.190       0.850
older            -15.83188   64.94493  -0.244       0.807
no_school        -48.73703  123.22783  -0.396       0.693
some_primary     -39.83558  101.69344  -0.392       0.695
primary          162.64959  111.39240   1.460       0.145
wealth_bline      -0.12404    0.11993  -1.034       0.301
r                 66.46479   76.97005   0.864       0.388
wrdrecal_1       -11.72663   19.79709  -0.592       0.554
ravens            -5.83692   29.16114  -0.200       0.841
finlit_total     -47.84181   30.01856  -1.594       0.111
deathinfam       -80.38727  165.02896  -0.487       0.626
delta_income       0.01773    0.03515   0.504       0.614
delta_hh_tot_exp   0.01178    0.02147   0.549       0.583
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 625.9 on 647 degrees of freedom
Multiple R-squared:  0.01855,	Adjusted R-squared:  -0.002685
F-statistic: 0.8736 on 14 and 647 DF,  p-value: 0.588
```

Model validation

```
Call:
lm(formula = loss.1 ~ male + younger + older + +no_school + some_primary +
    morethan_primary + wealth_bline + r + wrdrecal_1 + ravens +
    finlit_total + deathinfam + delta_income + delta_hh_tot_exp,
    data = mydataset)

Residuals:
   Min     1Q Median     3Q    Max
-936.2 -397.5 -104.3  203.8 3206.8

Coefficients:
                   Estimate Std. Error t value          Pr(>|t|)
(Intercept)      1015.89361  139.12597   7.302 0.000000000000836 ***
male              -49.77443   55.11703  -0.903           0.36683
younger            11.64881   61.42851   0.190           0.84966
older             -15.83188   64.94493  -0.244           0.80748
no_school        -211.38662   97.98723  -2.157           0.03135 *
some_primary     -202.48517   75.35626  -2.687           0.00739 **
morethan_primary -162.64959  111.39240  -1.460           0.14473
wealth_bline       -0.12404    0.11993  -1.034           0.30140
r                  66.46479   76.97005   0.864           0.38817
wrdrecal_1        -11.72663   19.79709  -0.592           0.55383
ravens             -5.83692   29.16114  -0.200           0.84142
finlit_total      -47.84181   30.01856  -1.594           0.11148
deathinfam        -80.38727  165.02896  -0.487           0.62635
delta_income        0.01773    0.03515   0.504           0.61416
delta_hh_tot_exp    0.01178    0.02147   0.549           0.58333
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 625.9 on 647 degrees of freedom
Multiple R-squared:  0.01855,	Adjusted R-squared:  -0.002685
F-statistic: 0.8736 on 14 and 647 DF,  p-value: 0.588
```

Model validation

```
Call:
lm(formula = loss.1 ~ male + younger + older + +yesed + wealth_bline +
    r + wrdrecal_1 + ravens + finlit_total + deathinfam + delta_income +
    delta_hh_tot_exp, data = mydataset)

Residuals:
   Min     1Q Median     3Q    Max
-821.2 -397.8 -108.4  216.5 3207.5

Coefficients:
                   Estimate Std. Error t value        Pr(>|t|)
(Intercept)      767.952359 113.463606   6.768 0.0000000000292 ***
male             -29.579962  54.809698  -0.540           0.590
younger            6.865915  59.543494   0.115           0.908
older            -16.593211  65.207823  -0.254           0.799
yesed             32.798769  72.290848   0.454           0.650
wealth_bline      -0.093468   0.119854  -0.780           0.436
r                 64.954027  77.040916   0.843           0.399
wrdrecal_1        -7.507623  19.812652  -0.379           0.705
ravens            -2.232835  28.874697  -0.077           0.938
finlit_total     -30.132138  28.739543  -1.048           0.295
deathinfam       -66.821465 165.621278  -0.403           0.687
delta_income       0.028229   0.035058   0.805           0.421
delta_hh_tot_exp   0.006995   0.021479   0.326           0.745
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 628.4 on 649 degrees of freedom
Multiple R-squared:  0.007505,  Adjusted R-squared:  -0.01085
F-statistic: 0.409 on 12 and 649 DF,  p-value: 0.9604
```

Model validation

```
Call:
lm(formula = loss.2 ~ male + younger + older + no_school + some_primary +
    primary + wealth_bline + r + wrdrecal_1 + ravens + finlit_total +
    deathinfam + delta_income + delta_hh_tot_exp, data = mydataset)

Residuals:
    Min       1Q   Median       3Q      Max
-1203.2   -589.8   -258.2    287.9   6232.7

Coefficients:
                    Estimate  Std. Error t value    Pr(>|t|)
(Intercept)      1298.775787  248.322979   5.230 0.000000229 ***
male               37.912260   85.938636   0.441       0.659
younger            40.119712   95.779517   0.419       0.675
older             -75.445487  101.262331  -0.745       0.457
no_school        -175.811585  192.137200  -0.915       0.361
some_primary      -87.846620  158.560709  -0.554       0.580
primary           -32.208671  173.683366  -0.185       0.853
wealth_bline        0.026257    0.186999   0.140       0.888
r                 -74.329607  120.011930  -0.619       0.536
wrdrecal_1        -22.134701   30.867680  -0.717       0.474
ravens             21.579117   45.468134   0.475       0.635
finlit_total      -28.843371   46.805034  -0.616       0.538
deathinfam       -378.258482  257.313653  -1.470       0.142
delta_income       -0.007301    0.054805  -0.133       0.894
delta_hh_tot_exp   -0.009073    0.033481  -0.271       0.786
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 975.9 on 647 degrees of freedom
Multiple R-squared:  0.009479,  Adjusted R-squared:  -0.01195
F-statistic: 0.4422 on 14 and 647 DF,  p-value: 0.9607
```

Model validation

```
Call:
lm(formula = loss.prime ~ male + younger + older + no_school +
    some_primary + primary + wealth_bline + r + wrdrecal_1 +
    ravens + finlit_total + deathinfam + delta_income + delta_hh_tot_exp,
    data = mydataset)

Residuals:
    Min      1Q  Median      3Q     Max
-2912.6 -1047.8  -113.1   961.9  4973.0

Coefficients:
                  Estimate Std. Error t value  Pr(>|t|)
(Intercept)     1452.57156  336.20622   4.320 0.0000180 ***
male             197.05802  116.35292   1.694    0.0908 .
younger           23.98978  129.67656   0.185    0.8533
older           -140.02508  137.09978  -1.021    0.3075
no_school        -60.83833  260.13590  -0.234    0.8152
some_primary      31.92374  214.67645   0.149    0.8818
primary           18.44248  235.15112   0.078    0.9375
wealth_bline       0.38872    0.25318   1.535    0.1252
r                719.65828  162.48499   4.429 0.0000111 ***
wrdrecal_1        64.51807   41.79197   1.544    0.1231
ravens            -9.08247   61.55962  -0.148    0.8828
finlit_total     141.95013   63.36966   2.240    0.0254 *
deathinfam      -193.66705  348.37875  -0.556    0.5785
delta_income       0.01891    0.07420   0.255    0.7989
delta_hh_tot_exp   0.02589    0.04533   0.571    0.5681
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1321 on 647 degrees of freedom
Multiple R-squared:  0.07094,   Adjusted R-squared:  0.05083
F-statistic: 3.529 on 14 and 647 DF,  p-value: 0.00001293
```

Model validation

```
Call:
lm(formula = dloss21 ~ male + younger + older + no_school + some_primary +
    primary + wealth_bline + r + wrdrecal_1 + ravens + finlit_total +
    deathinfam + delta_income + delta_hh_tot_exp, data = mydataset)

Residuals:
    Min      1Q  Median      3Q     Max
-2353.6  -431.2  -188.2   234.5  6857.2

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)
(Intercept)       445.53176  234.02879   1.904   0.0574 .
male               87.68669   80.99176   1.083   0.2794
younger            28.47090   90.26617   0.315   0.7526
older             -59.61361   95.43338  -0.625   0.5324
no_school        -127.07455  181.07723  -0.702   0.4831
some_primary      -48.01104  149.43350  -0.321   0.7481
primary          -194.85826  163.68565  -1.190   0.2343
wealth_bline        0.15030    0.17624   0.853   0.3941
r                -140.79440  113.10370  -1.245   0.2136
wrdrecal_1        -10.40807   29.09085  -0.358   0.7206
ravens             27.41603   42.85086   0.640   0.5225
finlit_total       18.99844   44.11080   0.431   0.6668
deathinfam       -297.87121  242.50194  -1.228   0.2198
delta_income       -0.02503    0.05165  -0.485   0.6281
delta_hh_tot_exp   -0.02086    0.03155  -0.661   0.5088
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 919.7 on 647 degrees of freedom
Multiple R-squared:  0.01481,   Adjusted R-squared:  -0.006506
F-statistic: 0.6948 on 14 and 647 DF,  p-value: 0.7806
```

Model validation

```
Call:
lm(formula = dloss2prime ~ male + younger + older + no_school +
    some_primary + primary + wealth_bline + r + wrdrecal_1 +
    ravens + finlit_total + deathinfam + delta_income + delta_hh_tot_exp,
    data = mydataset)

Residuals:
    Min      1Q  Median      3Q     Max
-3805.3  -748.9   348.1  1060.9  3749.2

Coefficients:
                  Estimate Std. Error t value   Pr(>|t|)
(Intercept)     -153.79577  352.72983  -0.436     0.6630
male            -159.14576  122.07135  -1.304     0.1928
younger           16.12994  136.04980   0.119     0.9057
older             64.57960  143.83785   0.449     0.6536
no_school       -114.97325  272.92086  -0.421     0.6737
some_primary    -119.77036  225.22721  -0.532     0.5951
primary          -50.65115  246.70815  -0.205     0.8374
wealth_bline      -0.36246    0.26562  -1.365     0.1729
r               -793.98789  170.47068  -4.658 0.00000388 ***
wrdrecal_1       -86.65277   43.84593  -1.976     0.0485 *
ravens            30.66159   64.58511   0.475     0.6351
finlit_total    -170.79350   66.48411  -2.569     0.0104 *
deathinfam      -184.59144  365.50061  -0.505     0.6137
delta_income      -0.02621    0.07785  -0.337     0.7364
delta_hh_tot_exp  -0.03497    0.04756  -0.735     0.4625
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1386 on 647 degrees of freedom
Multiple R-squared:  0.06913,   Adjusted R-squared:  0.04899
F-statistic: 3.432 on 14 and 647 DF,  p-value: 0.00002091
```

Regressions on beta

- Baseline regressions on beta: http://localhost:28709/session/viewhtml4c5c229272b1/index.html
- Regressions including (σ, δ): http://localhost:28709/session/viewhtml4c5c7e1b3bd3/index.html

Comparison with hyperbolic discounting

- It is possible to prove that there exists a perfect mapping between the non-stationary utility approach and non-constant discounting **if** we allow the discount factor to be increasing over time.
- The change in instantaneous utility can be indeed caused by a change in the value we assign to future.
- However, the model is agnostic on the topic and does not rule out other possible interpretations.

Comparison with hyperbolic discounting

- One might ask if relaxing constant discounting rather then stationary instantaneous utility would provide better fit.
- Since there exists a perfect mapping between the two problems, the answer is no **if** we allow the discount factor to be increasing over time.
- In this case, the loss functions would be equal.
- If we want to restrict our focus on hyperbolic discounting — as the literature usually does — the loss in fit will increase.
- The advantage of the non-stationary instantaneous utility framework is that both downwards shocks and upwards ones are plausible.
- The underlying economic intuition is more convincing if applied to utility rather than to discount factors.