Dynamic and Stochastic Rational Behavior

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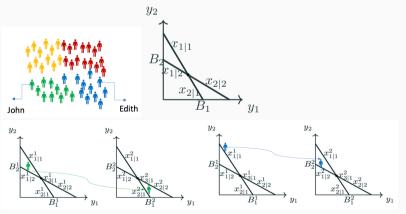
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Dynamic Random Utility Model (DRUM)

- Dynamic Random Utility Model–DRUM:
 - Each decision maker (DM) randomly draws a utility function from a stochastic utility process $(u^t)_{t\in\mathcal{T}}$ and maximizes it subject to a menu $(B^t)_{t\in\mathcal{T}}$ in each period.
 - Unrestricted time correlation and cross-section heterogeneity in preferences.
- Contribution: RP characterization of DRUM for a panel of choices and menus. New tech: converts static into dynamic models & obtains dynamic axiomatizations from their static counterparts.
- Static utility maximization is under scrutiny [Choi et al., 2007, Echenique et al., 2011, Ahn et al., 2014, Dean and Martin, 2016].
 - Evidence of changing taste [Cherchye et al., 2017, Adams et al., 2015], evolving errors in valuation [Kurtz-David et al., 2019], time varying risk aversion [Guiso et al., 2018].
- Our results unify static utility maximization—time series—[Afriat, 1967] and random utility—cross-section or pool—[McFadden, 2005, McFadden and Richter, 1990]. In experimental data, we show DRUM succeeds while static rationality fails.

Today Focus on Demand

- Simple-setup: 2 goods, T=2, and 2 budgets $B_j^{*t}=B_j^{*s}=B_j^*$, and $B_j^*\cap B_{j'}^*\neq\emptyset$.
- Patches are the **coarsest partition** of intersecting budgets in a period. WLG, dicretization.



 $\textbf{Budget path B_2^1, B_1^2. Choice path $x_{1|2}^1$, $x_{2|1}^2$. $\rho(x_{1|2}^1,x_{2|1}^2) + \rho(x_{1|2}^1,x_{2|1}^2) + \rho(x_{2|2}^1,x_{2|1}^2) + \rho(x_{2|2}^1,x_{2|1}^2) = 1$.}$

Setup

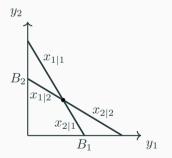
- Time: $\mathcal{T} = \{1, \dots, T\}, T \geq 1$. Finite choice set: X^t , endowed with $>^t$.
- At $t \in \mathcal{T}$, DM faces menu $B_{j_t}^t \in 2^{X^t} \setminus \emptyset$, with $j_t \in \mathcal{J}^t = \{1, \dots, J^t\}$ ($\mathbf{j} = \{j_t\}_{t \in \mathcal{T}}$). \mathbf{J} : menu paths.
- The i_t -th element of $j_t \in \mathcal{J}^t$ is $x_{i_t|j_t}^t$ with $i_t \in \mathcal{I}_j^t = \{1, \dots, I_j^t\}$ ($\mathbf{i} = (i_t)_{t \in \mathcal{T}}$). \mathbf{I}_j : choice paths.
- Primitive: $\rho_j \in \Delta(\prod_{t \in \mathcal{T}} B_{j_t}^t)$. $\rho_{\mathbf{j}}(x_{\mathbf{i}|\mathbf{j}}) \geq 0 \ \forall \ \mathbf{i} \in \mathbf{I_j}$, $\sum_{\mathbf{i} \in \mathbf{I_j}} \rho_{\mathbf{j}}(x_{\mathbf{i}|\mathbf{j}}) = 1$. $B_j^t = \{x_{i|j}^t\}_{i \in \mathcal{I}_j^t}$.
- U^t is the set of all injective, monotone on $>^t$ utility functions s.t. $u^t : X^t \to \mathbb{R}$ $(\mathcal{U} = \prod_{t \in \mathcal{T}} U^t)$.
- Dynamic stochastic choice function $\rho = (\rho_{\mathbf{j}})_{\mathbf{j} \in \mathbf{J}}$. ρ , is consistent with DRUM if $\exists \mu \in \Delta(\mathcal{U})$:

$$\rho_{\mathbf{j}}(x_{\mathbf{i}|\mathbf{j}}) = \int \prod_{t \in \mathcal{T}} 1(argmax_{y \in B_{j_t}^t} u^t(y) = x_{i_t|j_t}^t) d\mu(u), \forall \mathbf{i} \in \mathbf{I_j}, \mathbf{j} \in \mathbf{J}.$$

• E.g., (i) CD: $u^t(y_1, y_2) = y_1^{\alpha_t} y_2^{(1-\alpha_t)}$ with $\alpha_t = \alpha_{t-1} + \epsilon_t$. (ii) ERA $u^t(y_1, y_2) = \pi_1 \frac{y_1^{1-\sigma_t}}{1-\sigma_t} + (1-\pi_1) \frac{y_2^{1-\sigma_t}}{1-\sigma_t}$ with $\sigma_t \leq \sigma_{t-1}$. (iii) $u^t(x) = v(x) + \alpha_t' x$.

A Stochastic Revealed Preference Characterization of DRUM.

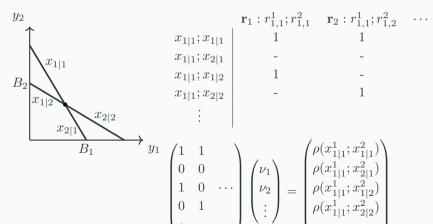
- DRUM is associated with a finite mixture over a finite number of preference profiles: $\mathbf{r} = \{r^1, \cdots, r^T\}, r^t$ is a linear order on patches.
- Assume away intersection patches. Static behavior summarized in A^t :



$r_{1,1}^{t}$	$r_{1,2}^{t}$	$r_{2,2}^{t}$	$r_{2,1}^t$
yes	yes	yes	no
1	1	-	-
-	-	1	1
1	-	-	1
-	1	1	-

A Stochastic Revealed Preference Characterization of DRUM.

- Encode \mathbf{r} , as $a_{\mathbf{r}} = (\prod_{t \in \mathcal{T}} a_{r^t, i_t, j_t})_{\mathbf{i} \in \mathbf{I_j}, \mathbf{j} \in \mathbf{J}}$. $a_{r^t, i_t, j_t} = 1 \iff x_{i_t | j_t}^{t*} = argmax_{y \in B_j^t} u^{r^t}(y)$. Matrix $A_T = \bigotimes_{t \in \mathcal{T}} A^t$.
- Recall $\rho(x_{\mathbf{i}|\mathbf{j}}) = \rho(\{x_{i_{\mathbf{i}}|j_{\mathbf{i}}}^t\}_{t\in\mathcal{T}})$, let $\rho = (\rho_{\mathbf{i}|\mathbf{j}})_{\mathbf{i}\in\mathbf{I}_{\mathbf{j}},\mathbf{j}\in\mathbf{J}}$.
- $A_T \nu = (A^1 \otimes A^2) \nu = \rho, \ \nu \in \Delta^8$ (i.e., 9 demand profiles types, A has dim. 16×9).



First Result: Axiom of Dynamic Stochastic Revealed Preference.

Definition

(Axiom of Dynamic Stochastic Revealed Preference, ADSRP) ρ satisfies ADSRP if for every finite sequence of pairs of budget and choice paths (including repetitions), k, $\{(i_k, j_k)\}$ such that $j_k \in J$ and $i_k \in I_{j_k}$

$$\sum_{k} \rho(x_{i_k|j_k}) \le \max_{r \in \mathcal{R}} \sum_{k} a_{r,i_k,j_k}.$$

Theorem

The following are equivalent:

- 1. ρ is consistent with DRUM.
- 2. There exists $\nu \in \Delta^{|\mathcal{R}|-1}$ such that $\rho = A_T \nu$.
- 3. There exists $\nu \in \mathbb{R}_+^{|\mathcal{R}|}$ such that $\rho = A_T \nu$.
- 4. ρ satisfies the ADSRP.

Computational Aspects of Testing

- Theorem 1.(3) $A_T \nu = \rho$ for $v \in \mathbb{R}_+^{|\mathcal{R}|}$ is straightforward to test using tools in [Kitamura and Stoye, 2018].
- Computational bottleneck: Computing A_T is costly [Smeulders et al., 2021].

Lemma

Let A^t be the matrix with entries $a^t_{r_t,i_t,j_t} = 1 \iff argmax_{y \in B^t_j} u^{r_t}(y) = x^t_{i_t|j_t}$, then $A_T = A^1 \otimes \cdots \otimes A^T$.

- If we have the same number of budgets, all intersecting $A_t = A_s$, then $A_T = A_1^{\otimes_{t=1}^{\prime}}$ (Kronecker power).
- Modular structure: computational savings. Kronecker product structure allows a linear inequality characterization.

Simple-setup necessary conditions: Stability

- (Stability) In the simple setup ρ satisfies stability if (i) $\rho(x_{l|k}^1; B_j^2) = \sum_{i \in \{1,2\}} \rho_{l|k;i|j}$ does not depend on B_j^2 , (ii) $\rho(x_{i|j}^2; B_k^1) = \sum_{l \in \{1,2\}} \rho_{l|k;i|j}$ does not depend on B_k^1 .
- If ρ is DRUM $\exists \nu \in \Delta^9$ s.t. $A_T \nu = \rho$. Verify:

t = 1; t = 2	$x_{1 1}$	$x_{2 1}$	$x_{1 2}$	$x_{2 2}$
$x_{1 1}$	$\rho_{1 1;1 1} = \nu_1 + \nu_2 + \nu_4 + \nu_5$	$\rho_{1 1;2 1} = \nu_3 + \nu_6$	$\rho_{1 1;1 2} = \nu_1 + \nu_4$	$\rho_{1 1;2 2} = \nu_2 + \nu_3 + \nu_5 + \nu_6$
$x_{2 1}$	$\rho_{2 1;1 1} = \nu_7 + \nu_8$	$\rho_{1 1;2 1} = \nu_9$	$\rho_{2 1;1 2} = \nu_7$	$\rho_{1 1;2 2} = \nu_8 + \nu_9$
$x_{1 2}$	$\rho_{1 2;1 1} = \nu_1 + \nu_2$	$\rho_{1 2;2 1} = \nu_3$	$\rho_{1 2;1 2} = \nu_1$	$\rho_{1 2;2 2} = \nu_2 + \nu_3$
$x_{2 2}$	$\rho_{2 2;1 1} = \nu_4 + \nu_5 + \nu_7 + \nu_8$	$\rho_{2 2;2 1} = \nu_6 + \nu_9$	$\rho_{2 2;1 2} = \nu_4 + \nu_7$	$\rho_{2 2;2 2} = \nu_5 + \nu_6 + \nu_8 + \nu_9$

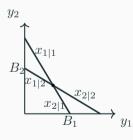
Simple-setup necessary conditions: Monotonicity

- Let $x_{i_{t}|i_{t}}^{t} >^{t} x_{l_{t}|k_{t}}^{t}$ if $x_{i_{t}|i_{t}}^{t*} > x_{l_{t}|k_{t}}^{t*}$.
- (Monotonicity) ρ satisfies monotonicity,

(i) if
$$x_{i'|j'}^1 >^1 x_{i|j}^1$$
 then $\rho(x_{i|j}^1, x_{l|k}^2) \le \rho(x_{i'|j'}^1, x_{l|k}^2)$, (ii) if $x_{l'|k'}^2 >^2 x_{l|k}^2$ then $\rho(x_{i|j}^1, x_{l|k}^2) \le \rho(x_{i|j}^1, x_{l'|k'}^2)$.

(ii) if
$$x_{l'|k'}^2 >^2 x_{l|k}^2$$
 then $\rho(x_{i|j}^1, x_{l|k}^2) \le \rho(x_{i|j}^1, x_{l'|k'}^2)$

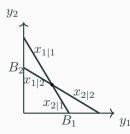
• For $\mathcal{T} = \{t\}$, Monotonicity is captured by a matrix H^t , s.t. $H^t \rho \geq 0$.



t = 1; t = 2	$x_{1 1}$	$x_{2 1}$	$x_{1 2}$	$x_{2 2}$
$x_{1 1}$	$\rho_{1 1;1 1} = \nu_1 + \nu_2 + \nu_4 + \nu_5$	$\rho_{1 1;2 1} = \nu_3 + \nu_6$	$\rho_{1 1;1 2} = \nu_1 + \nu_4$	$\rho_{1 1;2 2} = \nu_2 + \nu_3 + \nu_5 + \nu_6$
$x_{2 1}$	$\rho_{2 1;1 1} = \nu_7 + \nu_8$	$\rho_{2 1;2 1} = \nu_9$	$\rho_{2 1;1 2} = \nu_7$	$\rho_{1 1;2 2} = \nu_8 + \nu_9$
$x_{1 2}$	$\rho_{1 2;1 1} = \nu_1 + \nu_2$	$\rho_{1 2;2 1} = \nu_3$	$\rho_{1 2;1 2} = \nu_1$	$\rho_{1 2;2 2} = \nu_2 + \nu_3$
$x_{2 2}$	$\rho_{2 2;1 1} = \nu_4 + \nu_5 + \nu_7 + \nu_8$	$\rho_{2 2;2 1} = \nu_6 + \nu_9$	$\rho_{2 2;1 2} = \nu_4 + \nu_7$	$\rho_{2 2;2 2} = \nu_5 + \nu_6 + \nu_8 + \nu_9$

Simple-setup: D-Monotonicity

- D-monotonicity: Improving a dominant choice path has a higher impact on the probability of choosing a choice path than improving a dominated path.
 - $\bullet \ \ D^1(x^1_{i'|j'})[\rho(x^1_{i|j},x^2_{l|k})] = \rho(x^1_{i'|j'},x^2_{l|k}) \rho(x^1_{i|j},x^2_{l|k}) \geq 0 \ \text{if} \ x^1_{i'|j'} >^1 x^1_{i|j}.$
 - $D^2(x_{l'|k'})D^1(x_{i'|j'}^1)[\rho(x_{i|j}^1,x_{l|k}^2)] = [\rho(x_{i'|j'}^1,x_{l'|k'}^2) \rho(x_{i|j}^1,x_{l'|k'}^2) \rho(x_{i|j}^1,x_{l'|k'}^2)] [\rho(x_{i'|j'}^1,x_{l|k}^2) \rho(x_{i|j}^1,x_{l|k}^2)] \ge 0 \text{ if } x_{l'|k'}^2 >^2 x_{l|k}^2 \text{ and } x_{i'|j'}^1 >^1 x_{i|j}^1.$
- D-monotonicity iff $\otimes_{t \in \mathcal{T}} H^t \rho \geq 0$ (Kronecker product of Static Conditions!).
- E.g., (i) $\rho_{1|1;1|2} \rho_{1|1;1|1} \le \rho_{1|2;1|2} \rho_{1|2;1|1}$; (ii) $\rho_{2|2;1|2} \rho_{2|2;1|1} \le \rho_{2|1;1|2} \rho_{2|1;1|1}$



t = 1; t = 2	$x_{1 1}$	$x_{2 1}$	$x_{1 2}$	$x_{2 2}$
$x_{1 1}$	$\rho_{1 1;1 1} = \nu_1 + \nu_2 + \nu_4 + \nu_5$	$\rho_{1 1;2 1} = \nu_3 + \nu_6$	$\rho_{1 1;1 2} = \nu_1 + \nu_4$	$\rho_{1 1;2 2} = \nu_2 + \nu_3 + \nu_5 + \nu_6$
$x_{2 1}$	$\rho_{2 1;1 1} = \nu_7 + \nu_8$	$\rho_{1 1;2 1} = \nu_9$	$\rho_{2 1;1 2} = \nu_7$	$\rho_{1 1;2 2} = \nu_8 + \nu_9$
$x_{1 2}$	$\rho_{1 2;1 1} = \nu_1 + \nu_2$	$\rho_{1 2;2 1} = \nu_3$	$\rho_{1 2;1 2} = \nu_1$	$\rho_{1 2;2 2} = \nu_2 + \nu_3$
$x_{2 2}$	$\rho_{2 2;1 1} = \nu_4 + \nu_5 + \nu_7 + \nu_8$	$\rho_{2 2;2 1} = \nu_6 + \nu_9$	$\rho_{2 2;1 2} = \nu_4 + \nu_7$	$\rho_{2 2;2 2} = \nu_5 + \nu_6 + \nu_8 + \nu_9$

Simple-setup: A simpler characterization.

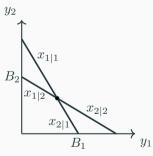
Theorem

For the simple-setup, the following are equivalent:

- 1. ρ is consistent with DRUM
- 2. ρ satisfies (i) stability, (ii) D-monotonicity.
- 3. ρ satisfies stability and $\otimes_{t \in \mathcal{T}} H^t \rho \geq 0$.
- This thm provides an explicit H-representation of DRUM. D-mon is not only monotonicity on each time period, it's more!
- D-mon is a dynamic version of the Weak Axiom of Stochastic Revealed Preference for the static case [Hoderlein and Stoye, 2014] and a stochastic version of the Weak Axiom of Revealed Preference.
- In this paper, we show the intution of $1 \iff 3$ holds generally in a general abstract domain.

Simple-setup: Counterexample of DRUM ρ

- $\rho_1^*(x_{2|1}^1, B_1^2) = \frac{1}{2}$, $\rho_1^*(x_{1|2}^1, B_1^2) = \frac{1}{2}$; and $\rho_1^*(x_{2|1}^1, B_2^2) = \frac{1}{3}$ and $\rho_1^*(x_{1|1}^1, B_2^2) = \frac{2}{3}$.
- Static case with 2 goods: RUM rationalizability is equivalent to $\rho_1^*(x_{2|1}^1,B_j^2) \leq \rho_1^*(x_{1|1}^1,B_j^2)$.
- Yet, stability, monotonicity, and IM are violated.



t = 1; t = 2	$x_{1 1}$	$x_{2 1}$	$x_{1 2}$	$x_{2 2}$
$x_{1 1}$	$\frac{1}{6}$	$\frac{1}{3}$	$\frac{2}{3}$	0
$x_{2 1}$	$\frac{2}{6}$	$\frac{1}{6}$	$\frac{1}{6}$	$\frac{1}{6}$
$x_{1 2}$	$\frac{1}{6}$	$\frac{1}{3}$	$\frac{2}{3}$	0
$x_{2 2}$	$\frac{2}{6}$	$\frac{1}{6}$	$\frac{1}{6}$	$\frac{1}{6}$

Relation with Samuelson-Afriat: Static Utility Maximization.

- We say DRUM, is **constant** when $u_s = u_t$ almost surely $\forall t, s \in \mathcal{T}$.
- (Strong Axiom of Revealed Patch Dominance, SARPD) For $\mathbf{j} \in \mathbf{J}$, $p_{\mathbf{j}}$ satisfies SARPD if $\rho_{\mathbf{j}}(\{x_{i_t|j_t}^t\}_{t\in\mathcal{T}}) = 0$, when $\{x_{i_t|j_t}^t\}_{t\in\mathcal{T}}$ is such s.t. $x_{i_t|j_t}^{t*} \in x_{i_t|j_t}^t$,

$$p_{j_t}^{t\prime}x_{i_t|j_t}^{t*} \geq p_{j_t}^{t\prime}x_{i_s|j_s}^{**}, p_j^{s\prime}x_{i_s|j_s}^{**} \geq p_{j_s}^{s\prime}x_{i_r|j_r}^{r*}, \cdots, p_{j_r}^{r\prime}x_{i_r|j_r}^{**} \geq p_{j_r}^{r\prime}x_{i_k|j_k}^{k*}, \text{ and } p_{j_k}^{k\prime}x_{i_k|j_k}^{k*} \geq p_{j_k}^{k\prime}x_{i_t|j_t}^{t*}.$$

- Proposition: If ρ is consistent with a constant DRUM, then $p_{\mathbf{j}}$ satisfies SARPD for all $\mathbf{j} \in \mathbf{J}$.
- DRUM does not impose SARPD, but **it bounds** cycles: $\rho(x_{1|2}^1, x_{2|1}^1) \le \rho(x_{1|1}^1, x_{2|2}^2)$.

Relation with McFadden-Richter: Random Utility Model.

- Define: (marginal) $\rho_{t,\mathbf{j}}^m(x_{i_t|j_t}) = \sum_{\tau \in \mathcal{T} \setminus \{t\}} \sum_{i \in \mathcal{I}_{j_\tau}^{\tau}} \rho(x_{\mathbf{i}|\mathbf{j}}),$ (conditional) $\rho_{t,\mathbf{j}}^c(x_{i_t|j_t}) = \frac{\rho(x_{\mathbf{i}|\mathbf{j}})}{\sum_{i \in \mathcal{I}_{j_t}^{\tau}} \rho(x_{\mathbf{i}|\mathbf{j}})},$ (slice) $\rho_t^s(x_{i_t,j_t}) = \sum_{\mathbf{j} \in \mathbf{J}} \rho_{t,\mathbf{j}}^m(x_{i_t|j_t}) F(\mathbf{j}|j_t),$ where $F(\mathbf{j}|j_t)$ is the conditional probability of budget path.
- **Proposition:** If ρ is consistent with DRUM, then $\rho_{t,\mathbf{j}}^m$, $\rho_{t,\mathbf{j}}^c$ and ρ_t^s are rationalized by RUM for any t and any $\mathbf{j} \in \mathbf{J}$.
- RUM has "less empirical content" than DRUM by ignoring the time dimension.

Relation with the Literature.

- DRUM was introduced by [Strzalecki, 2021], but the characterization was an open question. The problem is hard! We solved it with a new mathematical technique. Also, we study more domains such as demand.
- [Chambers et al., 2021, Li, 2021] characterize models of "correlated choice" in a discrete choice set environment with menu variation (i.e., no monotonicity, and choice sets are assumed to be nested). This does not work in demand analysis. We provide a characterization for their setup in full generality. Chambers et. al assume T=2 and assume additional structure in one period, and Li assumes $|X^t| \leq 3$.

Conclusions.

- DRUM is a powerful framework for choice analysis: modular/compositional, more informative than McFadden-Richter, yet more flexible than Samuelson-Afriat.
- DRUM synthesizes the static utility maximization model and the random utility framework.
- DRUM, as opposed to the static utility maximization, does not require acyclicity. Yet it bounds revealed demand cycles. It needs panel datasets.
- RUM can be satisfied in "pooled" data, but DRUM can fail. This means RUM is missing some empirical bite from stochastic rationality.

For Further Reading i

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Stochastic Choice.
Mimeo.

Simple-setup: A simpler characterization (proof (i)).

•
$$\mathcal{T} = \{t\}.$$
 $\rho = A^t \nu = \begin{pmatrix} 1 & 1 & 0 \\ 0 & 0 & 1 \\ 1 & 0 & 0 \\ 0 & 1 & 1 \end{pmatrix} \begin{pmatrix} \nu_1 \\ \nu_2 \\ \nu_3 \end{pmatrix} = \begin{pmatrix} (\nu_1 + \nu_2) \\ \nu_3 \\ \nu_1 \\ (\nu_2 + \nu_3) \end{pmatrix} \implies \rho(x_{1|1}^t) \ge \rho(x_{1|2}^t).$

•
$$\rho = A_T \nu = A^1 \otimes A^2 \nu = \begin{pmatrix} A^1 & A^1 & 0 \\ 0 & 0 & A^1 \\ A^1 & 0 & 0 \\ 0 & A^1 & A^1 \end{pmatrix} \begin{pmatrix} \nu_1^1 \\ \nu_2^1 \\ \nu_3^1 \end{pmatrix} = \begin{pmatrix} A^1 (\nu_1^1 + \nu_2^1) \\ A^1 \nu_3^1 \\ A^1 (\nu_2^1 + \nu_3^1) \end{pmatrix} \Longrightarrow$$

•
$$\implies [\rho(x_{1|1}^1, x_{1|1}^2) - \rho(x_{1|2}^1, x_{1|1}^2)] - [\rho(x_{1|1}^1, x_{1|2}^2) - \rho(x_{1|2}^1, x_{1|2}^2)] \ge 0.$$

Simple-setup: A simpler characterization (proof (ii)).

• For the simple setup $\mathcal{T} = \{t\}$, ρ is consistent with RUM iff $H^t \rho \geq 0$ iff ρ satisfies monotonicity.

$$\bullet \ \ H^t = \left(\begin{array}{cccc} x_{1|1}^t & x_{2|1}^t & x_{1|2}^t & x_{2|2}^t \\ 1 & 0 & -1 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{array} \right); H^t \rho \geq 0; \rho(x_{1|1}^t) \geq \rho(x_{1|2}^t) + \text{nonnegativity of } \rho.$$

- We apply our general mathematical result that says that in this case, ρ is consistent with DRUM iff $(\otimes_{t \in \mathcal{T}} H^t) \rho \geq 0$.
- ρ is consistent with D-monotonicity iff $(\otimes_{t \in \mathcal{T}} H^t) \rho \geq 0$.

Dynamic Random Augmented Utility Model, DRAUM

- Consider $X^* = X \times \mathbb{R}_-$ corresponding to consumption and the expenditure on it. Let F_{X^*} be the set of measurable sets on X^* ($F_{X^*}^T = \prod_{t \in \mathcal{T}} F_X$). Let \mathbf{j} index a price path $(p_j^1, p_j^2, \cdots p_j^t)$. $\rho_{X^*, \mathbf{j}}$ is a measure on $F_{X^{*T}}$
- $\rho_{X^*,j}$, is rationalized by a probability measure η over \mathcal{V} $(v=(v^t)_{t\in\mathcal{T}}\in\mathcal{V},)$ if

$$\rho_{X^*,j}(\{O^t\}_{t\in\mathcal{T}}) = \int \prod_{t\in\mathcal{T}} 1(argmax_{y\in\mathbb{R}_+^K} v^t(y, -p_j^{t'}y) \in O^t) d\eta(v), \forall \mathbf{j}, \{O^t\}_{t\in\mathcal{T}}.$$

- Consider the random augmented utility: $\mathbf{v}^t(x, -p^{t'}x) = u(x) + \delta E[V(\mathbf{y}_t + (1+r_t)s_{t-1}(\mathbf{y}) p^{t'}x)|I_t]$, randomness comes from the information I_t .
- If we assume this information is i.i.d. and independent of prices then this is a special case of DRAUM.
- All our characterization works for DRAUM for transformed patches. See [Deb et al., 2021].

General Axiomatization of DRUM: given RUM

- Define A^{t*} as the submatrix of A^t . Take A^t and delete the last row of each menu.
- We say A^t generates a **unique RUM** when the system $\rho = A^t \nu$ has a unique solution. Unique DRUM defind. analogously.
- $C^{\otimes k} = \bigotimes_{j=1}^k C$. $\phi^t = \frac{1}{|rows|} \sum_{row} H_{row}^t$, $\gamma_k^{\phi^t} = \frac{1}{k} \sum_{j=1}^k \phi^{t,\otimes(j-1)} \otimes I^t \otimes \phi^{t,\otimes(k-j)}$, $\Gamma_k^{\phi} = I^1 \otimes (\bigotimes_{t \in \mathcal{T} \setminus \{1\}} \gamma_{k_t}^{\phi^t})$.

Theorem

Assume that A^{t*} is full row rank for all $t \in \mathcal{T}$. Then ρ is consistent with DRUM if and only if ρ is stable and

$$\rho \in \bigcap_{k_1, \cdots, k_T} \left\{ \Gamma_k^{\phi^{*'}} z : \left(\otimes H^{t, \otimes_{k_t}} \right) z \right\}.$$

Moreover, ρ is consistent with unique DRUM if and only if ρ is table and $(\otimes_{t \in \mathcal{H}} H^t) \rho \geq 0$.

 Given, H^t ∀t, we get linear and closed-form necessary and sufficient conditions for DRUM with arbitrary precision.