A DYNAMIC DISCRETE-CONTINUOUS CHOICE MODEL FOR CAR OWNERSHIP AND USAGE

ESTIMATION PROCEDURE

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- Introduction
- Contributions
- Model specification & estimation
- Swedish registers
- Estimation on synthetic & real data
- Conclusion and future works





Objective

Model households' simultaneous choices of car ownership, usage and fuel type, assuming they are forward-looking.





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- Governmental policies to reduce carbon emissions / car usage (e.g. congestion taxes, independence of fossil fuels,...)
- Technology changes (e.g. increase of alternative-fuel vehicles)
- Variations in economic factors (e.g. fuel price changes)





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Case study: Swedish registers of vehicles and individuals

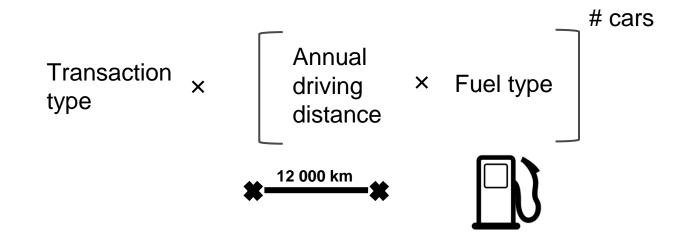






Objective

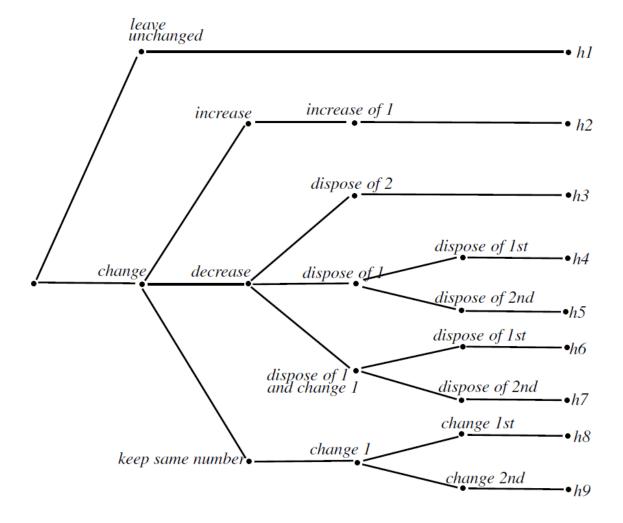
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Transaction type (0-, 1-, 2-car households)



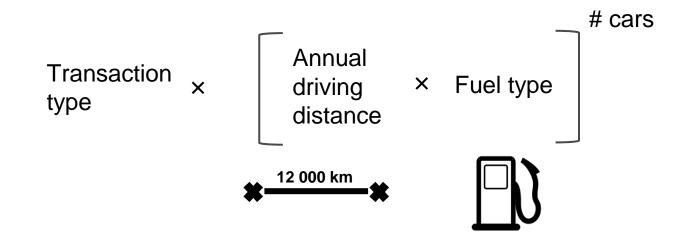






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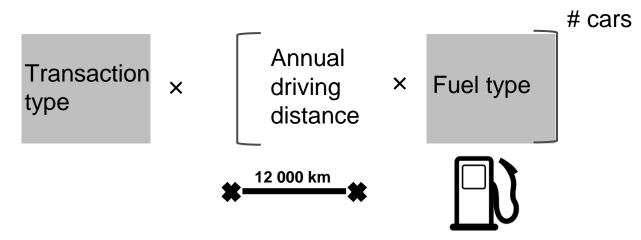






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Discrete variables

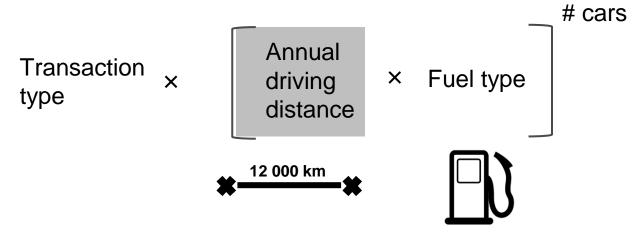






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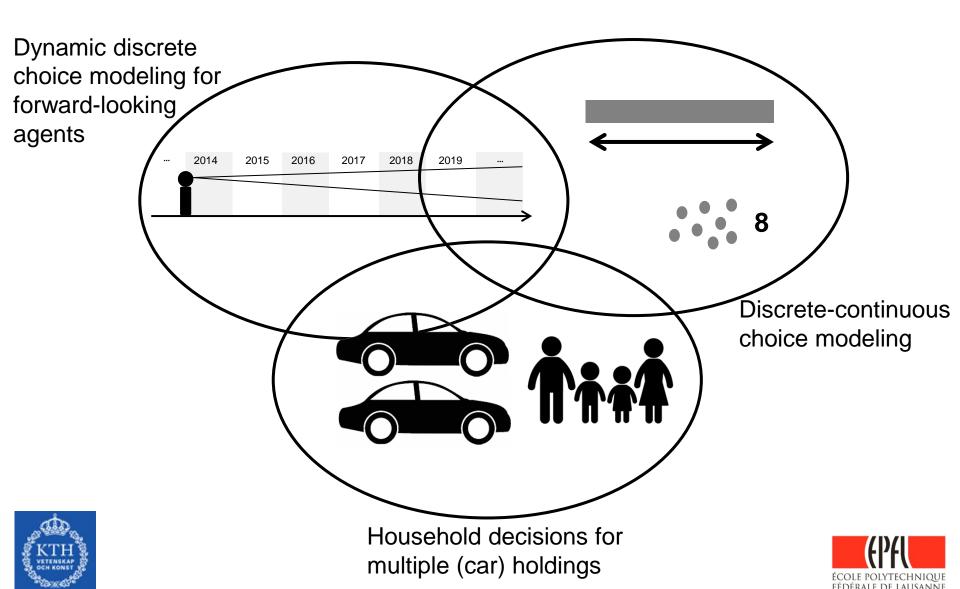


Continuous variables

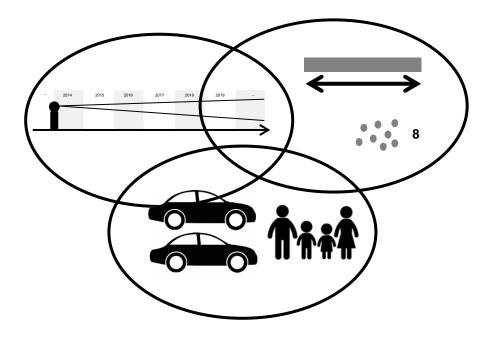




The method brings together 3 complex aspects of demand modeling



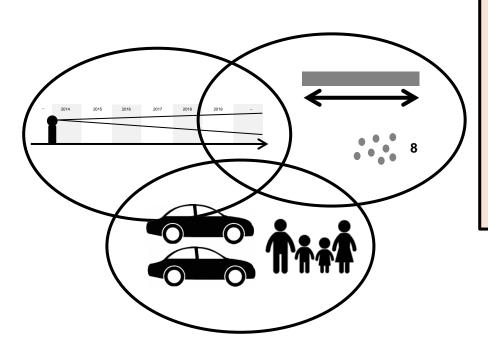
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Methodology

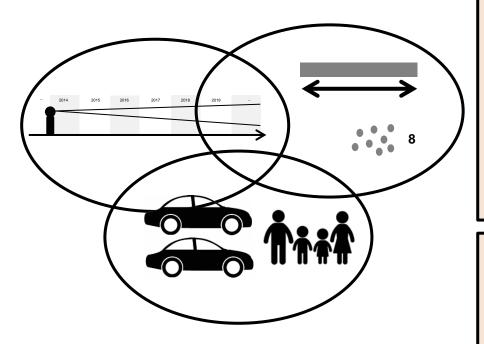
Address these issues by applying dynamic discrete-continuous choice model (DDCCM)

- Discrete-continuous choice model
- Embedded into a dynamic programming framework





The method brings together 3 complex aspects of demand modeling



Methodology

Address these issues by applying dynamic discrete-continuous choice model (DDCCM)

- Discrete-continuous choice model
- Embedded into a dynamic programming framework

Application example

Large **register data** of all **individuals** and **cars** in Sweden

- Approach validated on synthetic data
- Estimation on real data





ASSUMPTIONS

- 1. Choice at household level: up to 2 cars in household
- 2. Strategic choice of:
 - Transaction
 - Fuel type(s)
 - Account for forward-looking behavior of households
- 3. Myopic choice of:
 - Annual driving distance(s)





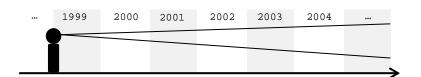
ASSUMPTIONS

Myopic choice (static case)



$$P(\text{action}) = \frac{\exp\{\text{instantaneous utility}\}}{\sum_{\text{all poss. actions}} \exp\{\text{instantaneous utilities}\}}$$

Strategic choice (dynamic case)



$$P(\text{action}) = \frac{\exp\{\text{instantaneous utility} + \text{expected discounted utility of future choices}\}}{\sum_{\text{all poss. actions}} \exp\{\text{instantaneous utilities} + \text{expected discounted utilities of future choices}\}}$$





DEFINITION OF THE COMPONENTS

Components of the DDCCM

- Agent
- Time step
- State space
- Action space
- Transition rule
- Instantaneous utility function





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Fundamental components in a dynamic programming framework





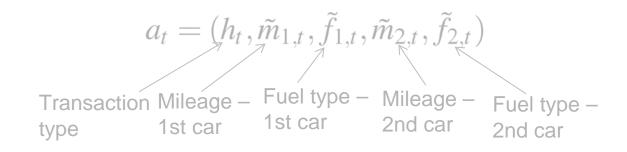
DEFINITION OF THE COMPONENTS

Agent: household



Time step t. year

Action space A



Transition rule: deterministic rule: each state s_{t+1} can be inferred exactly once s_t and a_t are known.





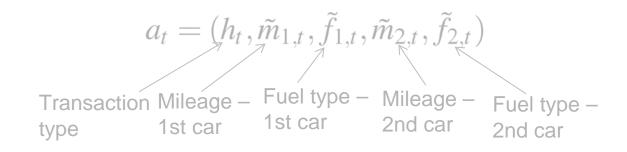
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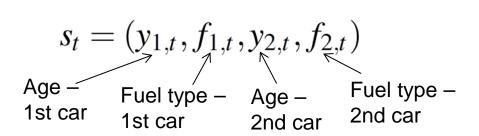
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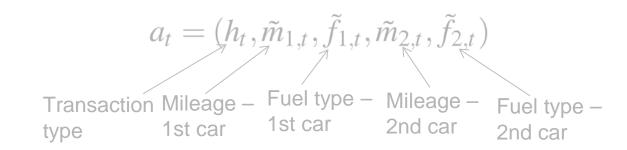
• Time step t. year

2009 2010

State space S



Action space A



• Transition rule: deterministic rule: each state s_{t+1} can be inferred exactly once s_t and a_t are known.





DEFINITION OF THE COMPONENTS

Agent: household



Time step t: year

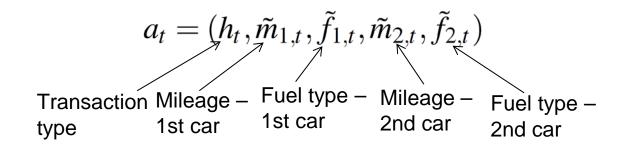
State space
$$S$$
 $s_t = (y_{1,t}, f_{1,t}, y_{2,t}, f_{2,t})$

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$$S_t$$

Action space A



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DEFINITION OF THE COMPONENTS

Agent: household

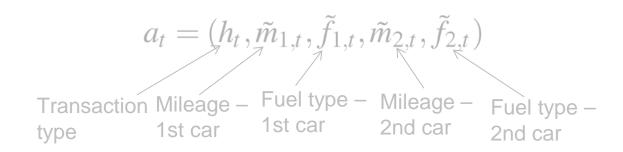


Time step t. year



State space S
$$s_t = (y_{1,t}, f_{1,t}, y_{2,t}, f_{2,t})$$
Age — Fuel type — Age — Fuel type — 2nd car 2nd car

Action space A



Transition rule: deterministic rule: each state s_{t+1} can be inferred exactly once s_t and a_t are known.





DEFINITION OF THE COMPONENTS

Instantaneous utility function

Deterministic utility

$$v(s_t, a_t^C, a_t^D, x_t, \theta) = v_t^D(s_t, a_t^D, x_t, \theta) + v_t^C(s_t, a_t^D, a_t^C, x_t, \theta)$$
Utility for the acquisition

Utility of driving acquisition

Constant elasticity of substitution (CES) utility function

$$v_t^C(s_t, a_t^D, a_t^C, x_t, \theta) = (m_{g,t}^{\rho} + m_{d,t}^{\rho})^{\frac{1}{\rho}}$$

Expected discounted utility

Choice probability
$$P(a_{n,t}^D|s_{n,t},x_{n,t},\theta) = \frac{v_{n,t}^D + v_{n,t}^{C*} + \beta \sum_{s_{n,t+1} \in S} \bar{V}f}{\sum_{a_{n,t}^D} \left\{ v_{n,t}^D + v_{n,t}^{C*} + \beta \sum_{s_{n,t+1} \in S} \bar{V}f \right\}}$$





Parameters obtained by maximizing likelihood:

$$\mathcal{L} = \prod_{n=1}^{N} \prod_{t=1}^{T_n} P(a_{n,t}^{D} | s_{n,t}, x_{n,t}, \theta)$$

- Optimization algorithm: Rust's nested fixed point algorithm (NFXP) (Rust, 1987):
 - Outer optimization algorithm: search algorithm to obtain parameters maximizing likelihood
 - Inner value iteration algorithm: solves the dynamic programming problem for each parameter trial





Outer algorithm

- Standard estimation procedure (as for static discrete choice models)
- Here: BHHH algorithm

Inner algorithm

Two steps

- Finding the optimal value(s) of annual mileage conditional on the discrete choices
- Finding the expected discounted utility of future choices (= value function)





1. Finding the optimal value(s) of mileage (e.g. 2-car households with different fuel types)

- Maximization of the continuous utility: $\max_{m_{g,t},m_{d,t}} v_t^C$ s.t. $p_{g,t}m_{g,t}+p_{d,t}m_{d,t}=Inc_t$
- Find analytical solutions $m_{g,t}^*$ and $m_{d,t}^*$.
- Optimal continuous utility $v_t^{C*}(s_t, a_t^D, a_t^{C*}, x_t, \theta)$

2. Finding the expected discounted utility of future choices (= value function)

- Logsum formula can be applied here given the key assumptions:
 - Choice of mileage(s) is conditional on discrete actions
 - Choice of mileage(s) is myopic

$$\bar{V}(s_t, x_t, \theta) = \log \sum_{a_t^D} \exp\{v_t^D(s_t, a_t^D, x_t, \theta) + v_t^{C*}(s_t, a_t^D, a_t^{C*}, x_t, \theta) + \beta \sum_{s_{t+1} \in S} \bar{V}(s_{t+1}, x_{t+1}, \theta) f(s_{t+1}|s_t, a_t)\}$$

• Iterate on Bellman equation to find integrated value function \overline{V}





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• Iterate on Bellman equation to find integrated value function $\overline{m{V}}$





SWEDISH REGISTERS

Register data of Swedish population and car fleet

- Data from 1998 to 2008
- All individuals
 - **Individual information**: socio-economic information on car holder (age, gender, income, home/work location, employment status/sector, etc.)
 - Household information: composition (families with children and married couples)
- All vehicles
 - Vehicle characteristics (make, model, fuel consumption, fuel type, age)
 - Annual mileage from odometer readings
 - Privately-owned cars, cars from privately-owned company and company cars
 - Car bought new or second-hand





Approach to validate the model framework

- Generate 5000 observations (households) based on distributions of variables in the Swedish register data
- Generate choice (for each observation) based on postulated parameters (10 different samples generated)
- Estimation of model on 10 samples
- Approach validated once postulated parameters are retrieved





Statistics on the Swedish register

Variable	Variable name	Level	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008
type												
Market	Average fuel	Gasoline	8.4	9.56	9.52	9.37	9.46	10.05	11.13	11.55	11.65	12.54
Market	price [SEK]	Diesel	6.66	8.44	8.69	8.36	7.92	8.61	10.48	11.27	10.88	13.12
		0 year	12.77	12.57	9.02	8.64	8.57	8.21	7.72	7.16	7.42	5.45
		1 year	11.55	13.53	13.45	9.72	9.18	9.25	9.03	8.64	8.24	8.73
		2 years	11.14	11.80	13.81	13.54	9.89	9.46	9.56	9.45	9.22	9.06
	C	3 years	9.70	11.70	12.42	14.11	13.71	10.40	9.99	10.21	10.16	10.28
Car fleet	Car age [% households]	4 years	8.90	9.73	11.99	12.46	13.82	13.66	10.62	10.35	10.63	11.01
		5 years	8.42	8.71	9.52	11.52	11.73	13.22	13.21	10.42	10.34	10.90
		6 years	6.70	8.08	8.43	9.06	10.72	11.10	12.64	12.76	10.25	10.43
		7 years	8.42	6.38	7.76	7.98	8.38	10.03	10.49	12.13	12.41	10.23
		8 years	10.18	7.95	6.08	7.30	7.34	7.82	9.42	9.98	11.74	12.30
		9 years	12.20	9.55	7.53	5.66	6.67	6.84	7.31	8.90	9.58	11.61
	Fuel type [%	Gasoline	97.23	97.04	97.10	97.05	97.01	96.96	96.91	96.47	95.37	94.44
	households]	Diesel	2.77	2.96	2.90	2.95	2.99	3.04	3.09	3.53	4.63	5.56
	N. 1 C	0 car	43.25	42.93	42.97	42.93	42.91	42.86	43.01	45.04	45.15	45.41
	Number of cars	1 car	44.96	44.76	44.69	44.65	44.57	44.44	44.20	42.54	42.35	42.11
Household	[% households]	2 cars	11.79	12.30	12.35	12.41	12.52	12.70	12.79	12.42	12.50	12.48
		Mean	185'508	197'706	201'695	210'277	214'197	218'315	226'946	232'715	254'452	259'523
	Income [SEK]	SD	321'885	667'570	631'202	429'462	298'663	237'607	224'982	465'895	338'340	981'006





Assumptions for the example

Deterministic utility function

$$v_t^D(s_t, a_t^D, x_t, \theta) = \tau(a_t^D) + \beta_{\mathrm{Age}}(a_t^D, s_t) \cdot \max(\mathrm{Age1}_t, \mathrm{Age2}_t)$$
 Transaction costs Transaction-dependant parameters relative to age of oldest car

Chose arbitrary values for parameters





			$eta_{ m Age}$		τ
Transaction name	Case	0 car	1 car	2 cars	all households
h_1 : leave unchanged		0	0	0	0
h_2 : increase 1		0	0	-	-3
h_3 : dispose 2		_	-	0	0
hu dianaga 1st	1st car is oldest	-	1.5	1.5	0
<i>h</i> ₄ : dispose 1st	2nd car is oldest	-	-	0	0
h : dispose 2nd	1st car is oldest	-	-	0	0
h_5 : dispose 2nd	2nd car is oldest	-	-	1.5	0
h_6 : dispose 1st and change 2nd		-	-	0	-4
h ₇ : dispose 2nd and change 1st		-	-	0	-4
L change 1st	1st car is oldest	-	1.5	1.5	-4
h ₈ : change 1st	2nd car is oldest	-	-	0	-4
h i ahanga 2nd	1st car is oldest	-	-	0	-4
h ₉ : change 2nd	2nd car is oldest	_	-	1.5	-4





Outcomes from synthetic data

		RI	no		Age								
						1 0	car		2 cars				
			_		Dispose/change				Dispose/change oldest car				
				t-test				t-test				t-test	
			t-test	true			t-test	true			t-test	true	
Run	Value	SD	0	value	Value	SD	0	value	Value	SD	0	value	
Synthetic data	0.49	0.03	14.10	-0.29	1.50	0.04	34.07	0.03	1.46	0.04	38.47	-0.93	
True value	0.5				1.5				1.5				
Initial value	0.5				1.5				1.5				
Real data	0.56	0.35	1.61	-	-0.52	0.04	-12.81	-	-0.17	0.05	-3.78	-	
Initial value	0.5				-0.55				-0.19				

		Transaction cost										
		Increa	se of 1		Dispose							
				t-test true				t-test true				
Run	Value	SD	t-test 0	value	Value	SD	t-test 0	value				
Synthetic data	-3.01	0.06	-50.74	-0.13	-3.99	0.05	-79.56	0.29	0.92			
True value	-3				-4							
Initial value	-3				-4							
Real data	-4.44	0.15	-30.13	-	-1.37	0.07	-18.49	-	7.17			
Initial value	-4.3				-1.33							



Tolerance synthetic data: 0.01

Tolerance real data: 0.8



ESTIMATION ON REAL DATA

Outcomes from real data

- Subsample of 446 households from merged registers of individuals and cars in Sweden
- 3431 observations





ESTIMATION ON REAL DATA

Outcomes from real data

		RI	ho		Age								
						1 (car		2 cars				
					Dispose/change				Dispose/change oldest car				
				t-test				t-test				t-test	
			t-test	true			t-test	true			t-test	true	
Run	Value	SD	0	value	Value	SD	0	value	Value	SD	0	value	
Synthetic data	0.49	0.03	14.10	-0.29	1.50	0.04	34.07	0.03	1.46	0.04	38.47	-0.93	
True value	0.5				1.5				1.5				
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Initial value	0.5				-0.55				-0.19				

		Transaction cost Dispose of 1 and change the other									
		Increa	se of 1		Dispose						
				t-test				t-test			
Run	Value	SD		true value	Value	SD		true value			
Synthetic data	-3.01	0.06							0.92		
True value	-3				-4						
Initial value	-3				-4						
Real data	-4.44	0.15	-30.13	-	-1.37	0.07	-18.49	-	7.17		
Initial value	-4.3				-1.33						



Tolerance synthetic data: 0.01

Tolerance real data: 0.8



CONCLUSION AND FUTURE WORKS

Contributions

Integrate three complex aspects of demand

- Forward-looking decision-makers
- Discrete-continuous choice: both fixed and operational costs are accounted for.
- Household decisions for multiple-car fleets

Next steps

- Further specification testing on the subsample of real data from Swedish registers
- Improvement of the optimization algorithm
- Scenario testing
 - Validation of policy measures taken during the years available in the data
 - Test policy measures that are planned to be applied in future years





Thank you!





Reasons of step 1.

Likelihood for the full model

$$L = \int P(D|C)f(C)dC$$

D = discrete variables

C = continuous variables



