Preview: Developing a Migration Module for the Demetra CGE

Notes prepared for the PANAP General Annual Meeting

Damiaan Persyn (damiaan.persyn@thuenen.de)

Thünen Institute and University of Göttingen, Germany

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Preview: Developing a Migration Module for the Demetra CGE

This is an upcoming collaboration with

- Dorothee Flaig, University of Hohenheim
- Scott McDonald, CGEMOD
- Emanuele Ferrari, JRC
- ...

Inspired by

- Report: Flaig and Persyn, 2021
- Econometric paper: Colen and Persyn, 2021/2022, MPRA 113385

In CGE models, migration is often modelled in an ad-hoc fashion.

- A function describes in-migration depending on local factors.
  - But what functional form? How to estimate parameters?
  - Keep track of population in origin
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- separate per sex,. . .
- what with several continuous explanatory variables?

- Our suggestion: use multinomial logit, statistical model for transition matrix

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$\rightarrow$

	A	B
A	$P(X_{od})$	$P(X_{od})$
B	$P(X_{od})$	$P(X_{od})$

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- Using nested logit for additional insight

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3 Additional insights:

- how to interpret coefficient on size in gravity equation (thanks to discrete-choice micro-foundation)
- how to combine multiple size variables
- attractive effect of dispersion/variation

Classic migration models (Harris&Todaro, 1970; Katz&Stark, 1986)

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Key observations:

- no role for size of locations ($e.g.\#jobs$)
- with risk-aversion, more variation makes a destination unattractive

Same in popular discrete choice migration models (Grogger and Hanson, 2011)

$$P = \frac{m_{od}}{pop_o} = \frac{exp(X_{od}\beta)}{\sum_d exp(X_{od}\beta)}$$

Assume $exp(X_{od}\beta) \equiv E[U_d]c_{od}$

$$\frac{m_{od}}{pop_o} = E[U_d]c_{od}\frac{1}{\sum_d E[U_d]c_{od}}$$

... note you can write this as a gravity equation. For example with $E[U_d] = w_d$

$$m_{od} = pop_o w_d c_{od}\frac{1}{\sum_d w_d c_{od}}$$

No role for size. Dispersion not attractive.

Compare this framework with how you would choose between holiday destinations.

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- You freely choose among all alternatives, in all countries. Bad alternatives (say boring or dangerous areas) are not relevant.
- You go to the country or region containing the single best alternative.
- A larger destination more likely contains your best alternative
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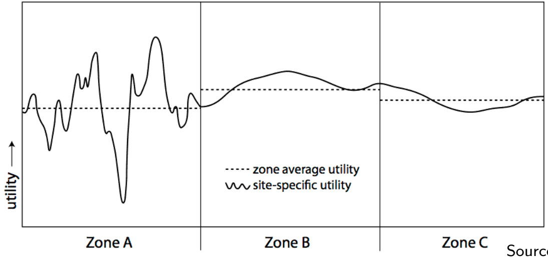
Similar for job-search: given a set of many offers, you ignore the bad offers, you move *after* you choosing the single best job offer. No need to consider expected value of randomly assigned job in each destination.



Source: Larch Documentation

- Destination A has a larger average utility (dotted) over all its locations compared to destination B.

  If you would be assigned a random location on arrival, better go to zone B!
- But if you can choose your preferred alternative within countries, zone A offers higher utility, just avoid the bad parts!

Takeaway: destinations offer a set of alternatives, and you can choose the best one, large destinations offering diverse alternatives are attractive. With uncertainty, other frameworks may be more relevant!

More formal, general: nested logit

McFadden 1978; Kanaroglou and Ferguson 1996; Train 2002.

$$P_d = \frac{\exp(w_d - c_{od} + \lambda_d I_d)}{\sum_e \exp(w_e - c_{oe} + \lambda_e I_e)} \qquad I_d = \log \sum_{g \in F_d} \exp(z_{gd}/\lambda_d).$$

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$w_d - c_{od} + \lambda_d I_d$: the utility you get from choosing destination d. It equals the *expected maximum utility* from being able to choose your preferred element from the set F_d in d:

$$V_d \equiv E[\max_{f \in F_d} U_{ofi}] = w_d - c_{od} + \lambda_d I_d.$$

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…for normally distributed alternatives $z_{fd} \sim \mathcal{N}(z_d, \sigma_d^2)$:

$$V_d = w_d + z_d - c_{od} + \lambda_d \log(N_d) + 0.5\frac{\sigma_d^2}{\lambda_d}.$$

Note: for $\sigma \to 0, \lambda \to 1$ we are back in the multinomial case (IIA holds)

Conclusion

Migration in CGE can be modelled using gravity equation

$$m_{od} = pop_o y_d N_d^{\lambda_d} \sigma_d^{0.5/\lambda_d} \phi_{od} \frac{1}{\sum_e y_e N_e^{\lambda_d} \sigma_d^{0.5/\lambda_d} \phi_{od}}.$$

Parameters can be estimated using Mult.logit or Poisson
Note role for destination size N_d, and dispersion in opportunities σ_d.

- $\lambda < 1$ indicates model has residual correlation between elements within d... add variables, or higher levels of nesting.
- Only for $\lambda = 1$ merging two destinations new predicted flow is simply sum of old flows. Predicted flow to ctr is sum of predicted flow to reg.
- Multiple mass variables can only enter with 'constant returns to scale' $N_1^{\alpha_1} N_2^{\alpha_2} \ldots$ and $\sum \alpha = 1$, or first aggregating in an index $N_1 + \alpha_2 N_2 + \alpha_3 N_3 + \ldots$ with an exponent $= 1$. (Daly 1982).
- Ceteris paribus, diverse opportunities makes a location attractive.

Empirical Application: internal migration in Ethiopia

Consider migration histories reported in Ethiopian LFS (240.000 obs.).
LFS data on

- individual chars.: gender, age, educ.
- zone and previous zone, rural/urban: 98 locations
- population of zone
- # paid jobs in zone (sometimes 0)

Combine LFS with

- data on number of houses with water (survey). Sometimes close to 0.
- data on dispersion in consumption (LSMS)

Empirical Application: internal migration in Ethiopia

- Use maximum likelihood estimation
- python BIOGEME (Bierlaire)

	(1)	(2)	(3)	(4)	(5)	(6)
log(pop)	0.48 (0.011)	0.472 (0.011)				
log(houses + $b_j$jobs)			0.767 (0.0065)	0.784 (0.00752)	0.775 (0.00768)	0.789 (0.00769)
b_j			0.479 (0.0248)	1.78 (0.17)	1.49 (0.14)	1.614 (0.16)
log(distance)	-1.72 (.0103)	-1.7 (0.0104)	-1.61 (0.00951)	-1.59 (0.0093)	-1.59 (0.00926)	-1.6 (0.00931)
log(cons)	2.07 (0.0246)	2.06 (0.0249)	0.838 (0.0195)	0.293 (0.0223)	0.31 (0.0223)	0.274 (0.022)
I(urban)				1.13 (0.0289)	1.05 (0.0288)	1.05 (0.03667)
Var(cons)						0.104 (0.00396)
I(same region)	-0.499 (0.0239)	-0.456 (0.0241)	0.0566 (0.0231)	0.0552 (0.023)	-0.0461 (0.0227)	0.354 (0.0479)
I(same region)·I(urban)					-0.136 (0.0431)	-0.18 (0.0434)
I(same region)·Var(cons)						0.174 (0.00882)
I(o=d)		2.91 (0.128)	3.52 (0.109)	4.29 (0.132)	6.92 (0.129)	2.45 (0.117)
I(o=d)·age	0.461 (0.0212)	0.248 (0.0104)	0.203 (0.00552)	0.242 (0.00691)	0.196 (0.0063)	0.181 (0.00614)
I(o=d)·educ	-1.72 (0.101)	-1.77 (0.0668)	-2.02 (0.0474)	-2.46 (0.059)	-1.92 (0.0691)	-1.8 (0.0669)
I(o=d)·I(female)	0.265 (0.0984)	-0.241 (0.0662)	-0.253 (0.056)	-0.306 (0.0665)	-0.239 (0.0513)	-0.222 (0.0502)
I(o=d)·I(urban)					-0.393 (0.096)	-0.595 (0.121)
I(o=d)·Var(cons)						0.247 (0.0289)
ξ	0.155 (0.00767)	0.242 (0.00936)	0.287 (0.00652)	0.242 (0.00587)	0.3 (0.00993)	0.323 (0.00978)
AIC	228336	227930	214915	213278	213208	212334
BIC	228413	228016	215011	213384	213333	212487
N	110615					

- choosing relevant mass & combining 2 mass variables: much better fit (AIC,BIC) coefficient closer to 1.
- control for dispersion: coefficient close to 0.5 in own region smaller when farther exactly as expected

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