The Design and Use of New Measures

Orazio P. Attanasio
Yale & NBER

Expectations and Learning in Dynamic Structural Model

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Outline

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- These *strong* assumptions were needed because preference and attitudes, beliefs and subjective expectations were largely perceived as unmeasurable.
- Skepticism towards questions that pose *hypothetical* situations and evidence from *stated* rather than *actual* choices.

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  - What are we measuring? What are we modelling?
    - Stigler and Becker (1977): "De Gustibus Non Est Disputandum".
      "... tastes neither change capriciously nor differ importantly between people'. [...] one does not argue over tastes for the same reason that one does not argue over the Rocky Mountains - both are there, will be there next year, too, and are the same to all men."

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- Block and Marschak (1960) on RUM, cited by Caplin (2012);
  - *''Our particular way of defining the class of basic observations and, correspondingly, of the directly testable conditions is to some extent arbitrary. Depending on the range of possible experiments and other observations, it may be preferable to define the class more narrowly [..] [or] more broadly. Following the practice of psychologists, we might admit the ranking, by the subject, of three or more objects as an observable fact, although the subject observed action consists in this case of a verbal statement. [..] We might even admit as observable the subject verbal statements of the relative intensity of his preferences''.*
- Stated preferences and conjoint analysis:
  - Luce (1956, 1959); Luce and Tukey (1964); Luce and Suppes (1965).

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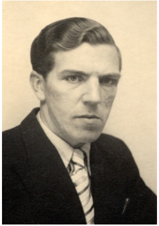
  Haavelmo (1958) presidential address is another important example:

I think most of us feel that if we could use *explicitly* such variables as, e.g., what people *think* prices or incomes are going to be, or variables expressing what people *think* the effects of their actions are going to be, we would be able to establish relations that could be more accurate and have more explanatory value. But because the statistics on such variables are not very far developed, we do not take the formulation of theories in terms of these variables seriously enough. It is my belief that if we can develop more explicit and a priori convincing economic models in terms of these variables, which are realities in the minds of people even if they are not in the current statistical yearbooks, then ways and means can and will eventually be found to obtain actual measurements of such data.



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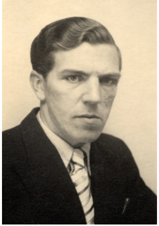

- ... but the consensus went towards an almost exclusive revealed preference approach.

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- Experimental economists have been trying a variety of different methods to measure *preferences*, *beliefs* and *attitudes*;
- Lab work on various mechanisms to elicit primitives.
- More recently experiments have been brought to the field and collected together with observational data to measure:
  - preference for and attitudes towards redistribution and attitudes towards migrants;
  - bargaining and social preferences;
  - reciprocity in conflict areas;
  - willingness to compete.

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Things have been changing

- There are some interesting discussions about what we could and should measure:
    - Contributions in the volume edited by Caplin and Schott (2008) and in particular the discussion between Gul and Pesendorfer for *mindless economics* v Camerer for *mindful economics*.
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  - Robustness;
  - Non-rational beliefs;
  - Learning.
- .... and some innovative work has been done in terms of measurement.
  - Eliciting data on policy preferences;
  - Eliciting data on information.

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- Measurement of subjective expectations.
  - Data on subjective expectations may allow avoiding strong assumptions.
  - These data are being used to estimate models of:
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- Measurement of beliefs and perceptions.
- Measurement of attitudes.
- Answers to questions about choices and events in counterfactual situations make the *identification* of structural models of behavior easier.

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This discussion is largely based on Almås, Attanasio, and Jervis (2024)

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- Measurement systems and the importance of measurement error
  - Measurement error is pervasive and important and should be recognized as such;
  - Augmenting the theoretical models we consider with a *measurement system* could be useful to the design of survey strategies.
  - Methodological issues in using factor models as measurement systems:
    - Metric and anchoring;
    - Cardinality.

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- Subjective expectations and their use
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- The quality of information and risk sharing
  - Quality of information in extended families networks in Tanzania.
- Parental investment and beliefs about the process of child development
  - A static model applied to Colombian data;
  - The adaptability of beliefs: learning in India.

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- Examples:
  - The work by Keynes, Kutznets, Stone, and others and the development of National Accounts: Keynes (1936); Kuznets et al. (1937); Kuznets (1941); Gilbert et al. (1949); Stone (1984).
  - Demand systems and price indexes: Stone (1954); Christensen et al. (1975); Deaton and Muellbauer (1980).

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  - Demand systems and price indexes: Stone (1954); Christensen et al. (1975); Deaton and Muellbauer (1980).
- For many years, the prevalent practice among most economists was the almost exclusive use of *choice* data, or objectively measureble variables
  - Consumption, income, prices, even anthropomteric....
  - ... but not attitudes, choices in hypothetical situations, beliefs, subjective expectations

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- Even at that time some researchers tried out and justified alternative measures;
  - Juster (1966) on buying intentions and purchasing probabilities;
  - Katona's work on the Michigan survey and consumer sentiment Katona (1974);
    - Curtin (2016) provides a nice survey;
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  - Juster and Shay (1964) hypothetical car loans to estimate the elasticity to maturity and interest rates.
- Revealed preferences become the main approach in economics:
  - Samuelson (1938, 1948); Arrow (1959)

> "I propose, therefore, that we start anew in direct attack upon the problem, dropping off the last vestiges of the utility analysis. This does not preclude the introduction of utility by any who may care to do so, nor will it contradict the results attained by use of related constructs. It is merely that the analysis can be carried on more directly and from a different set of postulates", Samuelson (1938).

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- An approach based *exclusively* on choice data can be very restrictive, as it precludes the analysis of important phenomena and of a wide sets of models.
- The use of such measurements should complement the use of choice data and such measures should be *validated*:
  - Samuelson (1938) ends his paper with:
    "In concluding this exposition, it may be well to sound a warning. Woe to any who deny any one of the three postulates* here! For they are, of course, deducible as theorems from the conventional analysis. They are less restrictive than the usual set-up, and logically equivalent to the reformulation of Hicks and Allen. It is hoped however, that the orientation given here is more directly based upon those elements which must be taken as data by economic science, and is more meaningful in its formulation."

* I. confronted with a given set of prices and with a given income, our idealised individual will always choose the same set of goods.

II. behaviour is independent of the units in which prices are expressed.

III. In any two price and income situations and corresponding quantities of consumer's goods given by equations (1.0) the individual must always behave consistently in the sense that (5.12) and (5.22) cannot hold simultaneously.

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- Manski (1990) argued that the issue is not *what* is being measured, but *the specific tools and questionnaires* being used.
- In the same paper, Manski notices that intention data, while not used much by economists, are widely used in other disciplines.

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- The use of data on subjective expectations and choices in counterfactual situations changes the nature of the residuals of the equations that are estimated and therefore the nature of identification.
- This is particularly relevant for the estimation of models with lagged dependent variables or selection.

Beyond standard measures

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- Data on:
  - Attitudes
  - Beliefs
  - Subjective expectations and counterfactuals

  need to be validated with choice data.

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Measurement error and its modeling

- The best approach to the difficulties of designing and implementing new measurement tools is to recognise explicitely the presence of measurement error.
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  - do the latent factors have cardinality?
- Some of these challenges can be tackled when designing questionnaires and their deployment.

A Measurement System for Child Development

- Suppose we are studying child development in the early years.
- Suppose we assume that child development has three dimensions:
    - Cognition and language;
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  - Cognition and language;
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  - Externalising Socio-emotional Skills.
- We can represent such a system as:

$$m_{i,t}^{jk} = \alpha_t^{j,k} + \beta_t^{j,k}\theta_{i,t}^{j} + \epsilon_{i,t}^{jk}, \quad j = 1, ...J; \;\; k = 1, ..., K.$$

- $\theta_{i,t}^{j}$ is factor j for individual i at time t;
- $m_{i,t}^{jk}$ is measure k for factor j;
- $\epsilon_{i,t}^{jk}$ is an *additive* measurement error ;
- $\alpha_t^{j,k}$ and $\beta_t^{j,k}$ are parameters representing the *discriminating* and *saliency* properties of a measurement item.

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  - At least 2 measures $m_{i,t}^{jk}$ per factor are available;
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  - Although non-parametric identification might be possible with enough measures, assumptions about the distribution of the factors $\boldsymbol{\theta}$ are typically used.
  - In this example, each measure is determined by only one factor.
  - This is a *dedicated* system;
  - This assumption can be somewhat relaxed.

Existing measures and measurement systems

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- This is analogous to the scoring algorithms that are often used in psychometrics, where a set of (often binary) variables are converted into a *score*.
- Often available measures use pre-defined scoring algorithms.
  - Examples of child development measures:
    - Bayley Scales of Infant Development; Woodcock Johnson; MacArthur-Bates Communicative Development Inventories (MB-CDIs).
  - These scoring algorithms were constructed calibrating on obsolete samples and/or are over-simplified.

Existing measures and measurement systems

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- Estimating an explicit measurement system from the individual available items also allows flexibility about functional form assumptions on the distribution of latent factors.

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Scaling: the importance of anchoring

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  - Normalise at least one of α's and one of the β's per factor;
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  - Normalise the mean and variance of the $\boldsymbol{\theta}$.
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  - e.g child development: height at 2 or wages at 22?
- The metric used to evaluate the unobserved latent factors is important:
  - Comparability across different contexts;
    - e.g. in measuring child development, comparing across different ages and measuring growth;
  - Evaluating the size of the impact achieved by certain interventions.

Scaling: the importance of anchoring

- Some of the normalisations are not innocuous:
    - Normalising $\beta_t^{jk} = 1, \ \forall t$ for a specific measure k is a very strong assumption.
    - Analogous considerations apply for the α's.
        - Agostinelli and Wiswall (2016) have some interesting work on this.
- The lack of longitudinal data covering long periods with the same measure is an additional problem.

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- Issues when different items are available over different ages or different cohorts.
  - Link adjacent ages with similar items to establish bridges over the entire life cycle,
    - Attanasio et al. (2020) look at child development from age 6 to 72 months.

Scaling: the importance of anchoring

- Some of the normalisations are not innocuous:
  - Normalising $\beta_t^{jk} = 1, \ \forall t$ for a specific measure k is a very strong assumption.
  - Analogous considerations apply for the α's.
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    - Attanasio et al. (2020) look at child development from age 6 to 72 months.
- This problem is common to many data sets.

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Cognitive Skills in the MCS	
Age 9 months	Denver Developmental Screening Test and MacArthur Communication Development Inventory
Age 3	Bracken Basic Concepts subscales (colours, etc) and British Ability Scales (BAS) Naming Vocabulary
Age 5	BAS Naming Vocabulary, Pattern Construction, and Picture Similarities scales
Age 7	BAS Pattern Construction, Word Reading scales, and NFER Number Skills
Age 11	BAS Verbal Similarities scale, Cambridge Gambling Task, and Spatial Working Memory
Age 14	Cambridge Gambling Task and Applied Psychology Unit Vocabulary test
Age 17	Number Analogies activity and GCSE grades by subject

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- This assumption can be insured by appropriate survey features:
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    - timing of data collection.
- More generally, the economic model one uses should dictate and direct:
    - the type of measures collected;
    - how they are collected.

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The design and use of subjective expectations data

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- This is based on work I have done with Manolo Arellano, Sam Crossman and Victor Sancibrian: Arellano, Attanasio, Crossman, and Sancibrián (2024)

The design and use of subjective expectations data

- My first example is about **measures of subjective expectations**.
- This is based on work I have done with Manolo Arellano, Sam Crossman and Victor Sancibrian: Arellano et al. (2024)
- Data on subjective expectations have become relatively common, following the path-breaking work of Manski (2004) and collaborators.
- It is now established that well designed questionnaires can be used to elicit the probability distribution of future uncertain variables.

  $\rightarrow$ it is possible to go beyond point expectations and obtain subjective probability distributions or subjective CDFs.

The design and use of subjective expectations data

- It is also possible to elicit *conditional* expectations of future events.
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- The existing evidence is that it is possible to obtain consistent and meaningful answers if questions posed properly.
- The 'right' way to ask questions may be context specific.
- Some preliminary questions can serve as 'training' of the respondents.

Using subjective expectations data

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- I will provide an example on a simple model of household income taken from some recent work from Arellano et al. (2024)

Data - India and Colombia

- For both India and Colombia, we use data on total household income expectations for poor households.
  - For India, we use data collected for the evaluation of a *microfinance intervention* (loans for cow or buffalo) in Andhra Pradesh.

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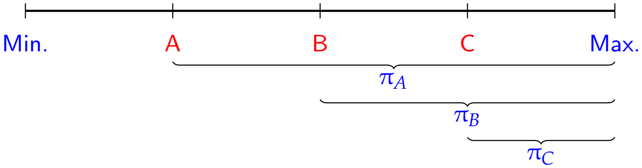
  - Income expectations refer to total household income *next month*.

Eliciting expectations

- In each wave of the surveys, subjective expectations about future income were elicited.
- First by asking the max. & min. possible income the household might earn over the next period.
- Then 3 probabilities are elicited using a ruler, π_A, π_B, π_C (as in Dominitz & Manski 1997 and others):

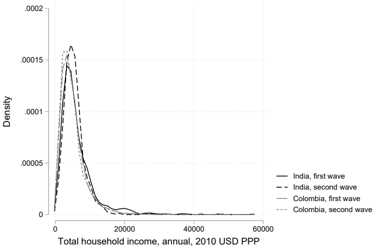


$$A = 0.75 * Min. + 0.25 * Max.; \quad B = 0.5 * (Min + Max.);$$

$$C = 0.25 * Min. + 0.75 * Max.;$$

Data

- Similar methods were used in India and Colombia.
- The main difference is that the expectations of future income refers to next month in Colombia and next year in India.
- In both cases these are very poor households.



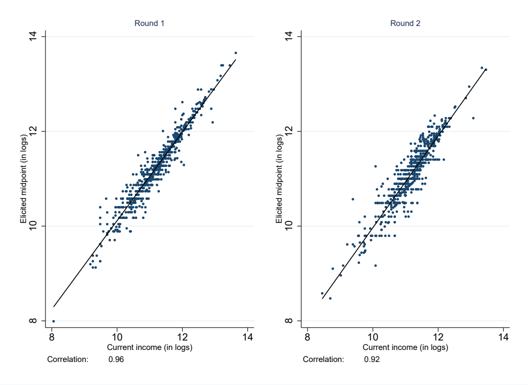
Note. The Figure shows the distribution of total household income in the two study populations, in 2010 PPP USD. Monthly income in Colombia is annualized for comparability.

Figure: Household income across study populations.

Validation : India

- To check whether the subjective expectations make sense we plot the subjective mean against actual income.

Figure: India: current income and reported midpoint



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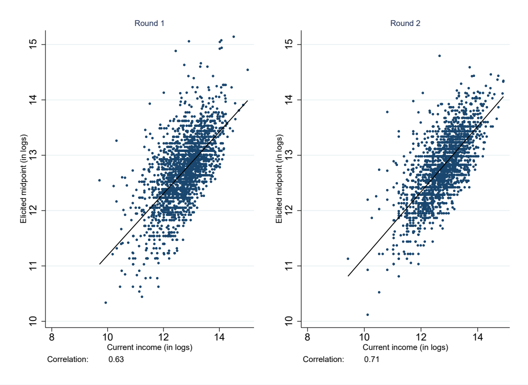

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- A household's subjective probability distribution of (log) future income $y_{i,t+1}$ is $F_{it}(r) = \Pr\left(y_{i,t+1} < r \mid I_{it}\right);\ I_{it}$ is the information available to household i at t.

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- The survey elicitation process yields noisy measurements p_{jit} of $F_{it}\left(r_{jit}\right)$ for $r_{jit} = r_{it}^{\text{min}} + \left(r_{it}^{\text{max}} - r_{it}^{\text{min}}\right) j/4\ (j = 1, 2, 3)$

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- We only observe 3 points of F_{it} for each unit, but many across units.
- We assume (plausibility) that elicitation errors are additive:

$$\ell_{jit} = \ell_{jit}^{*} + \varepsilon_{jit}$$

  where $\ell_{jit} = logit\left(p_{jit}\right)$ are the observed cumulative odds and ε_{jit} is an elicitation measurement error independent of I_{it}.
- The set I_{it} consists of time-varying and time-invariant characteristics.
- The time varying variables include observable current income y_{it} and indicators

Information set: time invariant variables

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- Therefore, our models take the form

$$\ell^*_{jit} = g\left(r_{jit}, y_{i,t}, x_{i,t}, \alpha_i\right) \qquad (i = 1, ..., n; j = 1, 2, 3; t = 1, 2)$$

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- We note that the individual effect α_i may be correlated with $\left(r_{jit}, y_{i,t}, x_{i,t}\right)$.

Linear model

- We first consider a linear autoregressive model with logistic shocks (ignoring $x_{i,t}$ for notational simplicity):

$$y_{i,t+1} = \rho y_{i,t} + \alpha_i + \sigma v_{i,t+1}$$
$$v_{i,t+1} \sim Logistic \text{ independent of } \left(y_{i,t}, \alpha_i\right).$$

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- The corresponding conditional *cdf* is:

$$\begin{aligned}\Pr\left(y_{i,t+1} \leqslant r \mid y_{i,t}, \alpha_i\right) &= \Pr\left(v_{i,t+1} \leqslant \frac{r - \rho y_{i,t} - \alpha_i}{\sigma} \mid y_{i,t}, \alpha_i\right) \\ &= \Lambda\left(\frac{r - \rho y_{i,t} - \alpha_i}{\sigma}\right).\end{aligned}$$

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- Therefore, in this case g is linear:

$$\ell_{jit} = \ell^*_{jit} + \varepsilon_{jit} = \beta_0 r_{jit} + \beta_1 y_{i,t} + \eta_i + \varepsilon_{jit},$$

where $\beta_0 = 1/\sigma$, $\beta_1 = -\rho/\sigma$ and $\eta_i = -\alpha_i/\sigma$.

Linear model: Using subjective expectation vs observed income

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  1. An AR(1) model without fixed effects can be estimated on a single cross-section, with subjective expectations., Two waves are needed for fixed effects.
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  2. Estimation of subjective expectation models does not suffer from Nickell bias.
     - The reason is that outcomes are not future incomes but points in the predictive distribution;
     - Therefore the error term does not contain future shocks but only measurement error in predictive probabilities.
  3. The subjective expectation approach does not force households to have rational expectations in the sense of optimal statistical forecasts.

Non linear models

- This model can be generalised to include non linearities and interactions with observables.
- In the paper we consider a version of the Arellano Blundell and Bonhomme (2017) model:

$$\ell_{jit} = \beta_0(r_{jit}) + \beta_1(r_{jit})\psi\left(y_{i,t}\right) + \beta_2(r_{jit})\eta_i + \varepsilon_{jit}$$

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- A similar approach can be used in estimation.
- Given the nonlinearity, the model properties will vary with the current income realisation, the quantile of the shocks and the distribution of fixed effects.
- We report:
  - Interquartile ranges;
  - The Bowley-Kelley measure of skewness for different quantiles;
  - The ABB measure of persistence:

$$\rho_{it}\left(\tau\right) = \frac{\partial q_{it}\left(\tau\right)}{\partial y_{i,t}} = -\frac{\partial g\left(q_{it}\left(\tau\right), y_{i,t}, x_{i,t}, \alpha_i\right)}{\partial y_{i,t}} \Big/ \frac{\partial g\left(q_{it}\left(\tau\right), y_{i,t}, x_{i,t}, \alpha_i\right)}{\partial r}.$$

Results: linear model

Models with or without fixed effects

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Indian data

- Measured persistence by ρ is around unity without fixed effects and 0.94 when fixed effects are included.
- The inclusion of fixed effects absorbs quite a bit of the variability in the estimated σ.

India: *linear AR(1): with and without fixed effects*

	No FE	FE
ρ	0.97	0.93
	(0.94, 1.00)	(0.90, 0.96)
σ	0.56	0.31
	(0.51, 0.60)	(0.29, 0.33)
$IQR_{0.75}$	1.22	0.69
	(1.13, 1.33)	(0.64, 0.74)
$IQR_{0.90}$	2.44	1.38
	(2.25, 2.65)	(1.29, 1.47)
σ^2_η		0.22
		(0.18, 0.27)
σ^2_η village		0.14
		(0.14, 0.19)
σ^2_ε	1.24	1.14
	(1.21, 1.27)	(1.10, 1.18)

Note. $n = 2230 \times 6$; 95% block bootstrap CI

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Colombian data

- Estimated ρ is close to unity without fixed effects, but the estimates are halved when fixed effects are included.

Colombia: *linear AR(1) with and without fixed effects*

	No FE	FE
ρ	0.71	0.50
	(0.67, 0.74)	(0.46, 0.55)
σ	0.98	0.65
	(0.93, 1.03)	(0.63, 0.67)
$IQR_{0.75}$	2.16	1.43
	(2.05, 2.26)	(1.38, 1.48)
$IQR_{0.90}$	4.31	2.86
	(4.10, 4.52)	(2.75, 2.96)
σ^2_η		0.48
		(0.44, 0.52)
σ^2_η village		0.12
		(0.12, 0.17)
σ^2_ε	1.46	1.09
	(1.42, 1.49)	(1.05, 1.12)

Note. $n = 2230 \times 6$; 95% block bootstrap CI

India: linear model with observable controls

- We first generalise the model adding controls on the sources of income and shocks.

$$\ell_{jit} = \beta_0 r_{jit} + \beta_1 y_{it} + \delta_0' x_{it} + \delta_1' x_{it} y_{it} + \eta_i + \varepsilon_{jit}.$$

ρ	$\leqslant$2 sources	3 sources	4+ sources
No shock	0.87	0.91	0.83
	(0.79, 0.95)	(0.84, 0.99)	(0.74, 0.93)
Health	0.92	0.97	0.89
	(0.86, 0.98)	(0.91, 1.04)	(0.81, 0.97)
Agricultural	0.90	0.97	0.87
	(0.86, 0.95)	(0.92, 1.01)	(0.81, 0.94)
Other	0.99	1.04	0.97
	(0.88, 1.09)	(0.93, 1.14)	(0.84, 1.08)
σ		0.30	
		(0.28, 0.32)	
$IQR_{0.90}$		1.34	
		(1.23, 1.42)	
σ^2_η		0.25	
		(0.22, 0.32)	
σ^2_η village		0.15	
		(0.15, 0.21)	
σ^2_ε		1.13	
		(1.08, 1.16)	

Note. n parenthesis we report 90% block bootstrap CI (1000 repetitions).

India: linear model with observable controls

- We first generalise the model adding controls on the sources of income and shocks.

$$\ell_{jit} = \beta_0 r_{jit} + \beta_1 y_{it} + \delta_0' x_{it} + \delta_1' x_{it} y_{it} + \eta_i + \varepsilon_{jit}.$$

ρ	$\leqslant$2 sources	3 sources	4+ sources
0% farm	0.87	0.90	0.83
	(0.83, 0.92)	(0.85, 0.95)	(0.76, 0.90)
50% farm	0.91	0.94	0.87
	(0.87, 0.95)	(0.90, 0.98)	(0.80, 0.93)
75% farm	0.93	0.96	0.89
	(0.88, 0.98)	(0.92, 1.01)	(0.82, 0.96)
σ		0.30	
		(0.28, 0.32)	
$IQR_{0.90}$		1.33	
		(1.24, 1.41)	
σ^2_η		0.23	
		(0.19, 0.28)	
σ^2_η village		0.13	
		(0.13, 0.18)	
σ^2_ε		1.12	
		(1.07, 1.16)	

Note. n parenthesis we report 90% block bootstrap CI (1000 repetitions).

Table: India — linear model augmented with household characteristics (shocks and income

Colombia: linear model with observable controls

- We first generalise the model adding controls on the sources of income and shocks.

$$\ell_{jit} = \beta_0 r_{jit} + \beta_1 y_{it} + \delta_0' x_{it} + \delta_1' x_{it} y_{it} + \eta_i + \varepsilon_{jit}.$$

ρ	1 earner	2 earners	3+ earners
0% regular	0.34	0.36	0.48
	(0.21, 0.48)	(0.24, 0.47)	(0.34, 0.63)
75% regular	0.51	0.52	0.61
	(0.43, 0.58)	(0.43, 0.59)	(0.51, 0.71)
100% regular	0.56	0.57	0.65
	(0.49, 0.63)	(0.48, 0.66)	(0.55, 0.76)
σ		0.64	
		(0.62, 0.67)	
$IQR_{0.90}$		2.83	
		(2.72, 2.92)	
σ^2_η		0.48	
		(0.45, 0.52)	
σ^2_η village		0.11	
		(0.12, 0.16)	
σ^2_ε		1.08	
		(1.04, 1.11)	

Note. n parenthesis we report 90% block bootstrap CI (1000 repetitions).

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ρ	1 earner	2 earners	3+ earners
No shock	0.54	0.55	0.58
	(0.47, 0.62)	(0.47, 0.63)	(0.48, 0.68)
Health	0.64	0.65	0.67
	(0.50, 0.77)	(0.51, 0.79)	(0.53, 0.81)
Other	0.44	0.46	0.48
	(0.32, 0.56)	(0.33, 0.58)	(0.34, 0.61)
σ		0.65	
		(0.62, 0.67)	
$IQR_{0.90}$		2.84	
		(2.73, 2.93)	
σ^2_η		0.48	
		(0.45, 0.53)	
σ^2_η village		0.11	
		(0.12, 0.16)	
σ^2_ε		1.09	
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Results on non-linear models: Colombia

- In the Colombian data introducing observables does matter for deviations from linearity.
- High persistence is concentrated among households with 3+ earners with low income and negative shocks.
- As in India, we observe skewness decreasing with income (ABB-like), but with values in the positive range.
- The linear AR(1) model is not as strongly rejected on the Colombian data as it was for India, but it can still be rejected.

Results on non-linear models: India

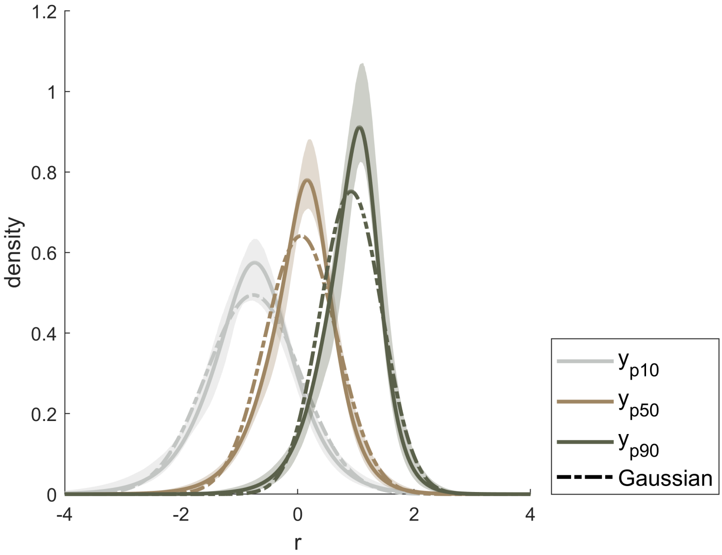
- We now consider a non-linear flexible model with additive fixed effects:

$$\ell_{jit} = \beta_0^{\dagger}(s_{jit}) + \beta_1^{\dagger}(s_{jit})\psi(y_{it}) + \eta_i + \varepsilon_{jit},$$

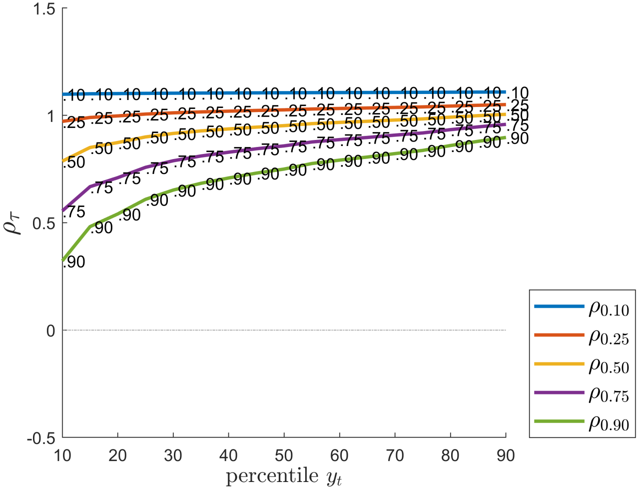
	$yp10$	$yp50$	$yp90$
$IQR_{0.75}$	0.56	0.46	0.42
	(0.49, 0.79)	(0.39, 0.56)	(0.33, 0.48)
$IQR_{0.90}$	1.31	1.04	0.90
	(1.04, 3.32)	(0.83, 1.50)	(0.70, 1.12)
$SK_{0.90}$	−0.25	−0.29	−0.29
	(−0.70, −0.04)	(−0.50, −0.11)	(−0.45, −0.12)
$\rho\ \tau 0.25$	1.00	1.05	1.07
	(0.93, 1.11)	(1.01, 1.10)	(1.03, 1.10)
$\rho\ \tau 0.50$	0.93	1.01	1.04
	(0.83, 0.97)	(0.95, 1.03)	(0.99, 1.06)
$\rho\ \tau 0.75$	0.82	0.97	1.02
	(0.63, 0.88)	(0.89, 0.99)	(0.95, 1.04)
σ^2_η		0.49	
		(0.38, 0.63)	
σ^2_η village		0.19	
		(0.18, 0.29)	
σ^2_ε		1.10	
		(1.01, 1.26)	

Note. In parenthesis we report 90% block bootstrap CI (1000 repetitions).

Density at different levels of current income



Persistence in India at different quantiles and at different current income



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	$yp10$	$yp50$	$yp90$
$IQR_{0.75}$	1.91	1.62	1.52
	(1.22, 4.19)	(1.11, 3.00)	(1.10, 2.41)
$IQR_{0.90}$	3.85	3.57	3.48
	(2.49, 8.13)	(2.39, 6.74)	(2.37, 6.18)
$SK_{0.90}$	0.37	0.27	0.16
	(0.21, 0.56)	(0.13, 0.50)	(0.05, 0.37)
$\rho\ \tau 0.25$	0.59	0.49	0.38
	(0.46, 0.69)	(0.26, 0.65)	(−0.07, 0.62)
$\rho\ \tau 0.50$	0.50	0.58	0.49
	(−0.31, 0.68)	(0.41, 0.68)	(0.20, 0.65)
$\rho\ \tau 0.75$	0.19	0.26	0.39
	(−1.24, 0.53)	(−0.72, 0.57)	(−0.39, 0.63)
σ^2_η		0.47	
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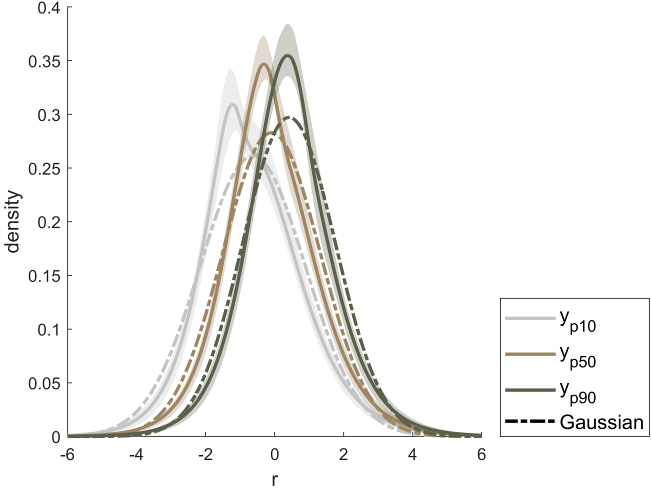
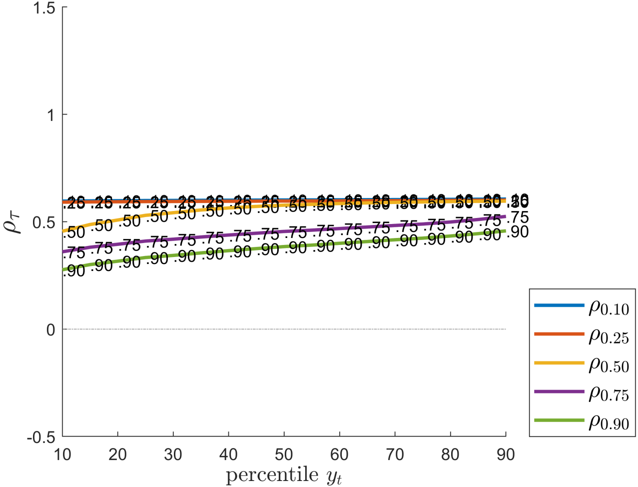
Density in Colombia at different level of current income



Note. The figure reports estimates of nonlinear persistence for Colombia for the flexible model with

Persistence in Colombia at different quantiles and at different current income



Outline

Information frictions in extended families in Tanzania

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  - Consider a new measure of network centrality constructed from the information quality measure and relate it to risk sharing and vulnerability to shocks.

The Tanzania KHDS data

- We use the Kagera Health and Development Survey (KHDS) - a unique longitudinal data set from Tanzania.
- Kagera is a relatively isolated region, far from the capital, where agriculture remains main source of income

The Tanzania KHDS data

- Study follows individuals from baseline (1991-1994 wave) sample of 915 households from 51 communities in Kagera region for 20 years
  - Wave 1991-94 (4 rounds)
  - Wave 2004
  - Wave 2010

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- Study follows individuals from baseline (1991-1994 wave) sample of 915 households from 51 communities in Kagera region for 20 years
    - Wave 1991-94 (4 rounds)
    - Wave 2004
    - Wave 2010
- Very rich and high quality data collected, including:
    - Demographics;
    - Consumption;
    - Income (including transfers) and wealth;
    - Reciprocal information on wealth indicators.
- Exceptionally low attrition due to huge tracking effort - 2010 sample includes at least one individual from 92% of baseline households

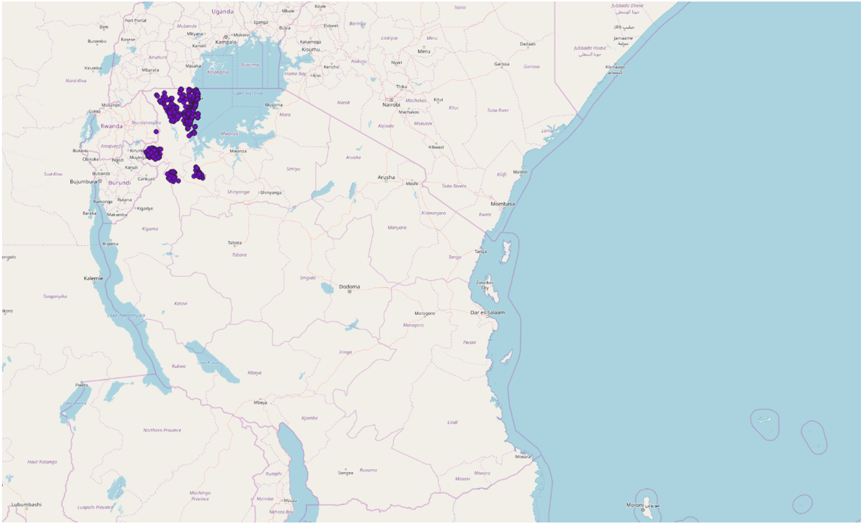


Figure: Sample 1991-1994

Figure: Sample 2004

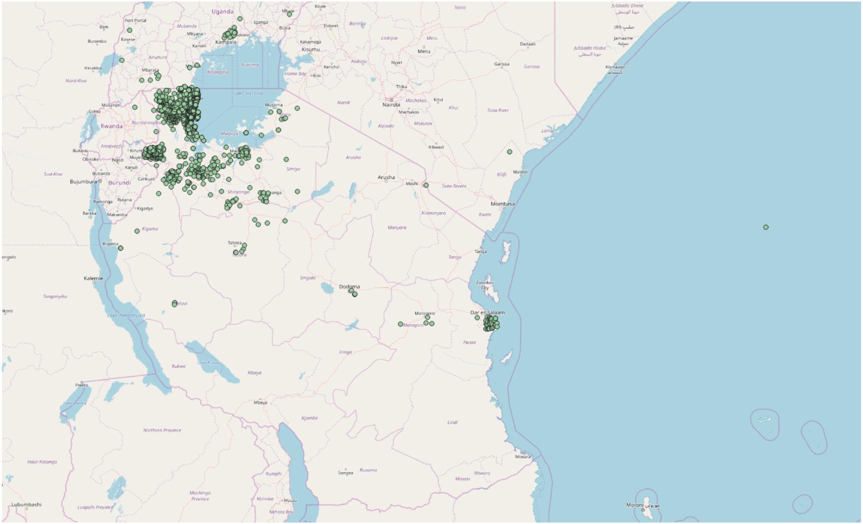
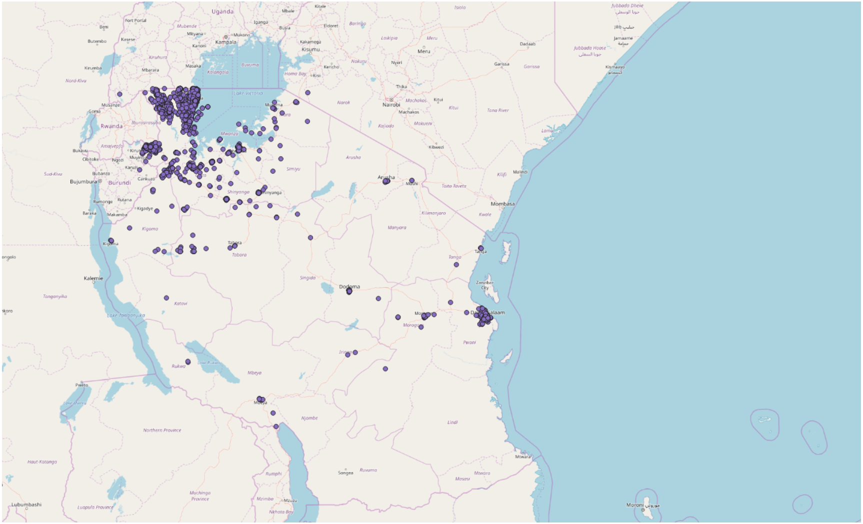


Figure: Sample 2010



Sample

Table: KHDS Sample

Round	HH	Ext HH	HH per Ex	Mean dist w/in HH
1991-1994	915	915	1	0
2004	2,774	831	3.34 (1.99)	74.74km (152.15)
2010	3,314	817	4.06 (2.38)	137.96km (185.63)

Wealth information

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- We are interested in questions about asset ownership of those individuals as a measure of their wealth and income.

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- We are interested in questions about asset ownership of those individuals as a measure of their wealth and income.
- Each household member is asked whether they own:
  1. house;
  2. land;
  3. oxen/bulls, dairy cows, non-dairy cows, other big livestock;
  4. phone (mobile or landline);
  5. video-equipment, TV, camera;
  6. Car, motorbike, other vehicle

Information on asset holding by other extended household members.

- All individuals within an extended family are also asked the same questions about the asset ownership by all other household members.
- It is therefore possible to compare:
  - actual asset ownership (as reported in the questionnaire)
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- This information can be used to construct measures of asymmetric information.

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- We judge the amount and quality of information among two individuals looking at the quality of information about assets.

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Measuring asymmetric information

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- The assumption is that discrepancies and imprecisions about asset ownership information reflect information about income flows and shocks.
- We use the available information on asset ownership to construct a 'wealth' index using an IRT model.
- This delivers, for each individual j belonging to household h, $\hat{\theta}_j^{jh} = \hat{f}(\mathbf{X}_j^{jh})$ where
  - the function $\hat{f}()$ is estimated from an IRT on asset ownership data
  - $\mathbf{X}_j^{jh}$ is the vector of ownership of different assets referring to individual j as declared by j themselves.

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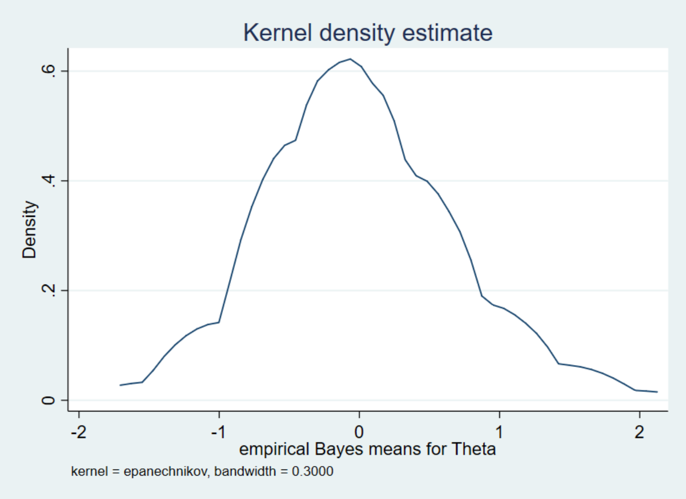
- Using parameters from "true" model (i.e. own assets) we construct an index for reported asset ownership.
- $\hat{\theta}_j^{kh} = \hat{f}(\mathbf{X}_j^{kh})$ is the wealth index for individual j as perceived by individual k in household h.

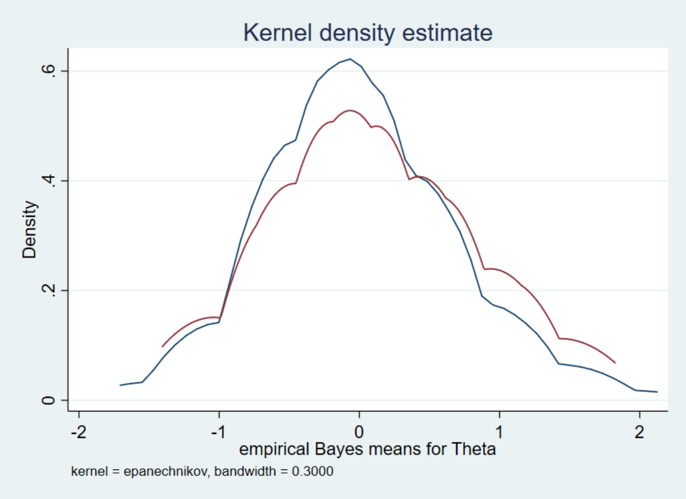
Distribution of wealth index from asset ownership

Figure: Kdensity of "true" asset ownership θ



Distribution of 'true' and 'perceived wealth index

Figure: Kdensity of "true" & "reported" asset ownership θ)



Asymmetric information

- Asymmetric information between j and k belonging to extended household g is approximated by the difference between the wealth indicator of individual j as estimated using own report and that estimated from the report of individual k about j's asset ownership.

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- In particular we consider 3 different measures:

$$\begin{aligned} q_{i,j}^{g,1} &= |\hat{\theta}_{i,g}^{i} - \hat{\theta}_{i,g}^{j}| \\ q_{i,j}^{g,2} &= |e^{\hat{\theta}_{i,g}^{i}} - e^{\hat{\theta}_{i,g}^{j}}| \\ q_{i,j}^{g,3} &= e^{|\hat{\theta}_{i,g}^{i} - \hat{\theta}_{i,g}^{j}|} \end{aligned}$$

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- For each of these measures, we construct an index that varies between 0 and 1:

$$\alpha_{ij}^{g,\ell} = \frac{1}{1 + q_{i,j}^{g,\ell}}, \quad \ell = 1, 2; \quad \alpha_{ij}^{g,3} = \frac{2}{1 + q_{i,j}^{g,3}}.$$

Properties of our measure of asymmetric information

	Mean	SD
Quality of information by distance btw households		
Q1 (0.4km)	0.97	0.11
Q2 (4.2km)	0.81	0.23
Q3 (17.2km)	0.75	0.24
Q4 (81.6km)	0.70	0.25
Q5 (613.5km)	0.67	0.24

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Quality of information by last time households spoke		
Less Than A Month Ago	0.86	0.21
Less Than A Year Ago	0.74	0.23
Less Than 2 Years Ago	0.71	0.25
Less Than 5 Years Ago	0.66	0.25
More Than 5 Years Ago	0.64	0.26
Don't Remember	0.59	0.26
N	12,693	

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  - $\alpha_{ij} = 1$ if individual i knows individual j.
  - Such matrices are then used to compute various properties of networks.
- In our analysis we construct adjacency matrices with $\alpha_{ij}^{g,\ell}$, $\ell = 1, 2, 3$.
  - We note that $\alpha_{ij}^{g} \in [0, 1]$
  - .... and these matrices can be asymmetric.

Network structures and position in the network

Asymmetric weighted adjacency matrixes

- Given the asymmetric information matrixes for each extended family, we can construct different properties for each network.

Network structures and position in the network

Asymmetric weighted adjacency matrixes

- Given the asymmetric information matrixes for each extended family, we can construct different properties for each network.
- Given an adjacency matrix $A^{g,\ell}$, we construct measures of their position in the network.
- We use measures of degree centrality, which can be obtained averaging, for each household, the elements of the row or the columns of the adjacency matrix.
- As the matrices are not symmetric, the measures obtained averaging the rows or the columns are different.

Network structures and position in the network

Asymmetric weighted adjacency matrix

- Averaging over the rows of the adjacency matrix $A^{g,\ell}$ we get the in-degree centrality, that is the average quality of the information the network has about the wealth of household i

$$InQ_i^{g,\ell} = \frac{1}{K_g - 1} \sum_{k \neq i} \alpha_{ik}^{g,\ell}$$

where K_g is the number of households in family g.

Network structures and position in the network

Asymmetric weighted adjacency matrix

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  where K_g is the number of households in family g.
- Analogously, we can construct the out-degree centrality measure for household i averaging the elements of the matrix $A^{g,\ell}$ corresponding to column i.

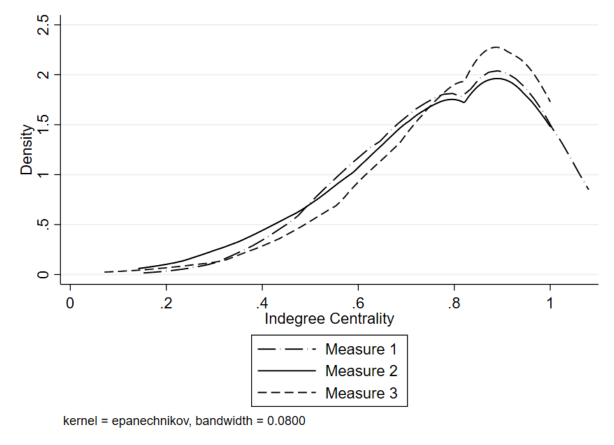
$$OutQ_i^{g,\ell} = \frac{1}{K_g - 1} \sum_{k \neq i} \alpha_{ki}^{g,\ell}$$

- Finally, we can also define the quality of information in family g averaging the individual measures as:

$$IQ^{g,\ell} = \frac{1}{K_g} \sum_{j}^{K_g} InQ_j^{g,\ell}$$

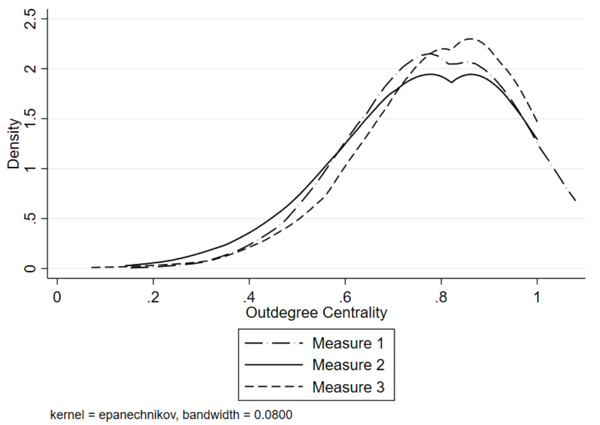
Descriptive statistics on the quality of information

Figure: Kdensity of $InQ_i^{h,\ell}$



Descriptive statistics on the quality of information

Figure: Kdensity of $OutQ_i^{h,\ell}$



Descriptive statistics on the quality of information

Table: Summary statistics and correlation matrix: network centrality measures

	Mean	SD	$InQ_i^{h,1}$	$InQ_i^{h,2}$	$InQ_i^{h,3}$	$OutQ_i^{h,1}$	$OutQ_i^{h,2}$	$OutQ_i^{h,3}$
Household level								
$InQ_i^{h,1}$	0.79	0.17	1.000					
$InQ_i^{h,2}$	0.77	0.20	0.944	1.000				
$InQ_i^{h,3}$	0.81	0.18	0.983	0.929	1.000			
$OutQ_i^{h,1}$	0.78	0.16	0.318	0.313	0.303	1.000		
$OutQ_i^{h,2}$	0.77	0.18	0.316	0.322	0.303	0.956	1.000	
$OutQ_i^{h,3}$	0.80	0.16	0.305	0.301	0.294	0.983	0.943	1.000
N	2,780							
Family network								
$IQ^{h,1}$	0.79	0.13						
$IQ^{h,2}$	0.77	0.15						
$IQ^{h,3}$	0.80	0.13						
N	709							

Risk sharing: a conceptual framework

- We start considering risk sharing within extended family g.
- Individual j belonging to household g receives a stochastic endowment $y_t^{j,g}$.

$$y_t^{j,g} = \bar{y^g}_t + \epsilon_t^j.$$

  - y is perishable: this can be easily relaxed, (we do not consider saving for simplicity here).

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  - y is perishable: this can be easily relaxed, (we do not consider saving for simplicity here).
  - $\bar{y^g}_t$ may include transfers received as a part of a risk sharing agreement with other families.

- Individual j receives utility from consumption c_t^j, which equals to their endowment plus a transfer τ_t^j, which can be negative :

$$c_t^j = y_t^{j,g} + \tau_t^j$$

Perfect risk sharing

- The implications under perfect risk sharing can be derived considering a social planner problem, as in Townsend (1994).

$$\max_{\{\tau_t^{i,g}\}^{i=1,..K_g}} \sum_{j=1}^{K_g} \lambda_{j,g} \sum_{t=0}^{\infty} \beta^t \int_Y u(y_t^{j,g} + \tau_t^{j,g}) d\mu^t(y_t^{j,g}) \qquad s.t.$$

$$\sum_{j=1}^{K_g} y_t^{j,g} = \sum_{j=1}^{K_g} c_t^{j,g} \quad \forall t \qquad\qquad c_t^{j,g} = y_t^{j,g} + \tau_t^{j,g} \quad \forall t, j$$

- $\lambda_{j,g}$ is the Pareto weight given to individual j, which allows for inequality and is assumed to be constant.
- $\mu^t()$ is a probability measure of the stochastic endowment y_t^j, which reflects the available (and public) information.
- $y_t^{j,g}$ is completely observable *(ex-post)* and can be contracted upon.

Perfect risk sharing

- The first order conditions for this problem, in the absence of frictions (information, enforceability) after taking logs are:

$$\lambda_{i,g} u'(c_t^{i,g})\beta^t = \nu_t^g$$

  with ν_t^g the multiplier of the aggregate resource constraint for group g.
- Note:
  - the right hand side, ν_t does not depend on j;
  - $\lambda_{i,g}$ does not depend on t.
  - the f.o.c. does not depend on $\mu^t()$: the condition applies in any state of the world and any history.

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- Taking logs:

$$ln(\lambda_{i,g}) + ln(u'(c_t^{i,g})) + tln(\beta) = ln(\nu_t^g)$$

- Taking differences across time periods:

$$\Delta_s ln(u'(c_t^{i,g})) + sln(\beta) = \Delta_s ln(\nu_t^g)$$

Testing perfect risk sharing

- Both the level and difference specifications do not depend on individual resources, controlling for group resources.
- These restrictions can be tested as in Townsend (1994):

$$ln(u'(c_t^{i,g})) = \tilde{\kappa}^{i,g} + ln(\nu_t^g) + \tilde{\gamma} ln(y_t^{i,g}) + \tilde{\epsilon}_t^{i,g}$$

$$\Delta_s ln(u'(c_t^{i,g})) = \kappa^g + \Delta_s ln(\nu_t^g) + \gamma \Delta_s ln(y_t^{i,g}) + \epsilon_t^{i,g}$$

where $\tilde{\epsilon}_t^{i,g}$ and $\epsilon_t^{i,g}$ reflect measurement error and other unobservables.

- The coefficients $\tilde{\gamma}$ and γ measure the *vulnerability* of a single individual to idiosyncratic shocks; they should be 0 under perfect risk sharing.
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- This test is based only on consumption and endowment data and does not require information about the decentralization.
- In the absence of income information, one can use data on idiosyncratic shocks.

Risk sharing and imperfect information

- We first estimate a version of the equation in differences.

$$\Delta_s ln(u'(c_t^{j,g})) = \nu_t^g + \gamma_{01} BS_t^{j,g} + \gamma_{02} GS_t^{j,g} + \epsilon_t^{j,g}$$

where γ_{01} and γ_{02} measure the effect of 'bad' and 'good' idiosyncratic shocks on changes in log consumption, which should be 0 under perfect risk sharing.

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- We then allow these coefficients depend on the *average quality of information* in group g.

$$\Delta_s ln(u'(c_t^{j,g})) = \nu_t^g + (\gamma_{01} + \gamma_{11} IQ^{g,\ell}) BS_t^{j,g} + (\gamma_{02} + \gamma_{12} IQ^{g,\ell}) GS_t^{j,g} + \epsilon_t^{j,g}$$

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- Finally, we consider the quality of the information available to individual j and of the about individual j: inward and outward degree centrality.

$$\Delta_s ln(u'(c_t^{j,g})) = \nu_t^g + (\gamma_{01} + \gamma_{21} IP_i^{g,\ell}) BS_t^{j,g} + (\gamma_{02} + \gamma_{22} IP_i^{g,\ell}) GS_t^{j,g} + \epsilon_t^{j,g}$$

$$\Delta_s ln(u'(c_t^{j,g})) = \nu_t^g + (\gamma_{01} + \gamma_{21} OP_i^{g,\ell}) BS_t^{j,g} + (\gamma_{02} + \gamma_{22} OP_i^{g,\ell}) GS_t^{j,g} + \epsilon_t^{j,g}$$

Risk sharing and network information quality

$$\Delta_s ln(u'(c_t^{j,g})) = \nu_t^g + (\gamma_{01} + \gamma_{11} IQ^{g,\ell}) BS_t^{j,g} + (\gamma_{02} + \gamma_{12} IQ^{g,\ell}) GS_t^{j,g} + \epsilon_t^{j,g}$$

Table: Sensitivity of risk-sharing to quality of information within family network

	(1)
Inf. quality measure	*none*
Bad shock in 2010	-0.134***
	(0.035)
Good shock in 2010	0.00289
	(0.036)
Good shock X mean degree cent $IQ^{h,\ell}$	
Bad shock X mean degree cent $IQ^{h,\ell}$	
Constant	0.434***
	(0.0125)
Observations	2,780

Risk sharing and network information quality

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Table: Sensitivity of risk-sharing to quality of information within family network

	(1)	(2)	(3)	(4)
Inf. quality measure	*none*	$IQ^{h,1}$	$IQ^{h,2}$	$IQ^{h,3}$
Bad shock in 2010	-0.134***	-0.420	-0.324	-0.324
	(0.035)	(0.256)	(0.223)	(0.223)
Good shock in 2010	0.00289	0.679***	0.561**	0.561**
	(0.036)	(0.262)	(0.227)	(0.227)
Good shock X mean degree cent $IQ^{h,\ell}$		-0.863***	-0.729**	-0.729**
		(0.332)	(0.293)	(0.293)
Bad shock X mean degree cent $IQ^{h,\ell}$		0.365	0.248	0.248
		(0.324)	(0.287)	(0.287)
Constant	0.434***	0.434***	0.434***	0.434***
	(0.0125)	(0.0240)	(0.0241)	(0.0241)
Observations	2,780	2,780	2,780	2,780

Standard errors in parentheses
Dep var = change in lnpcconsumption btw 2004-2010 (2010 prices); Family network FE
Shock = 1 if reported by anyone in household
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Risk sharing and asymmetric information

- This evidence shows that networks with better information quality are 'closer to perfect risk sharing' than networks with worse information.
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- This evidence is silent about possible risk sharing happening with other households or families *outside the network*.
- The next step is to look at evidence about the quality of information regarding individual households *in each network*
  - Inward degree centrality (how much the rest of the network knows about the household receiving a shock)
  - Outward degree centrality (how much an individual household knows about the rest of the network.

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- The next step is to look at evidence about the quality of information regarding individual households *in each network*
  - Inward degree centrality (how much the rest of the network knows about the household receiving a shock)
  - Outward degree centrality (how much an individual household knows about the rest of the network.
- These measures can be distinguished because the adjacence matrices are possibly asymmetric.

Risk sharing and in-degree centrality

$$\Delta_s ln(u'(c_t^{j,g})) = \nu_t^g + (\gamma_{01} + \gamma_{21} IP_i^{g,\ell}) BS_t^{j,g} + (\gamma_{02} + \gamma_{22} IP_i^{g,\ell}) GS_t^{j,g} + \epsilon_t^{j,g}$$

Table: Risk-sharing and quality of information family network has about affected households

	(1)	(2)	(3)	(4)
In-degree cent. measure	*none*	$InQ_i^{h,1}$	$InQ_i^{h,2}$	$InQ_i^{h,3}$
Bad shock in 2010	-0.134***	-0.457***	-0.426***	-0.419**
	(0.0350)	(0.164)	(0.146)	(0.164)
Good shock in 2010	0.00289	0.428**	0.279*	0.417**
	(0.0363)	(0.166)	(0.144)	(0.166)
HH indegree cent $InQ_i^{h,\ell}$		-0.337**	-0.252*	-0.327**
		(0.152)	(0.139)	(0.148)
Good shock X HH indegree cent $InQ_i^{h,\ell}$		-0.535***	-0.360**	-0.511**
		(0.206)	(0.182)	(0.202)
Bad shock X HH indegree cent $InQ_i^{h,\ell}$		0.413**	0.379**	0.357*
		(0.203)	(0.184)	(0.199)
Constant	0.434***	0.697***	0.627***	0.695***
	(0.0241)	(0.121)	(0.109)	(0.121)
Observations	2,780	2,780	2,780	2,780

Standard errors in parentheses
Dep var = change in lnpcconsumption btw 2004-2010 (2010 prices); Family network FE
Shock = 1 if reported by anyone in the household
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Risk sharing and out-degree centrality

$$\Delta_s ln(u'(c_t^{j,g})) = \nu_t^g + (\gamma_{01} + \gamma_{21} OP_i^{g,\ell}) BS_t^{j,g} + (\gamma_{02} + \gamma_{22} OP_i^{g,\ell}) GS_t^{j,g} + \epsilon_t^{j,g}$$

Table: Risk-sharing and quality of information affected households have about family network

	(1)	(2)	(3)	(4)
Out-degree centr. measure	*none*	$OutQ_i^{h,1}$	$OutQ_i^{h,2}$	$OutQ_i^{h,3}$
Bad shock in 2010	-0.134***	-0.139	-0.126	-0.0997
	(0.0350)	(0.185)	(0.160)	(0.186)
Good shock in 2010	0.00289	0.116	0.0852	0.162
	(0.0363)	(0.191)	(0.165)	(0.195)
HH outdegree cent $OutQ_i^{h,\ell}$		0.124	0.0523	0.195
		(0.183)	(0.161)	(0.180)
Good shock X HH outdegree cent $OutQ_i^{h,\ell}$		-0.144	-0.107	-0.200
		(0.239)	(0.209)	(0.238)
Bad shock X HH outdegree cent $OutQ_i^{h,\ell}$		0.00741	-0.0104	-0.0424
		(0.233)	(0.204)	(0.230)
Constant	0.434***	0.336**	0.393***	0.278*
	(0.0241)	(0.146)	(0.126)	(0.146)
Observations	2,780	2,780	2,780	2,780

Standard errors in parentheses
Dep var = change in lnpcconsumption btw 2004-2010 (2010 prices); Family network FE
Shock = 1 if reported by anyone in the household
$^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

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- Furthermore, it shows that what seems to matter is the quality of the information that the extended family *on average* has about the individual affected by a shock, whether positive or negative.
- Outward centrality does not matter.
- The next steps of this research is to provide a more structural interpretation to these results.

Risk sharing in networks: a more structural approach

- In a recent paper, Ambrus, Gao, and Milán (2021) consider risk sharing in a network.
- In their set-up, two members of a (potential) risk sharing group are either connected or not.
- If a connection exists, there is no asymmetric information, and endowment are fully observed.
- Transfers can only be contracted among members who are connected.

Risk sharing in networks.

- Ambrus et al. (2021) derive several important and interesting results, considering endowment processes with different levels of connections.
  - Pareto efficient allocations equalise *expected* ratios of marginal utility for each connected pair of individuals (conditional on local information).
  - The variability of consumption of a given individual depends on their position in the network.
  - More central individuals, in many situations, end up with more variable consumption.

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  - More central individuals, in many situations, end up with more variable consumption.
- Our data suggest an important extension: connections might not be 0/1 but could be stronger and weaker.
- This makes the theory more complex but, probably, more realistic.

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