The role of poverty on economic decision-making: a model of cognitive function and heuristic use.

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Abstract

Social scientists are increasingly interested in the question of whether living in poverty affects reasoning and decision-making. The role of stress on cognition, cognitive load and economic decision-making is a unifying domain of research across disciplines. The scarcity thesis argues that cognitive scarcity, in addition to actual resource scarcity, affects individuals' valuation of trade-offs and discounts. The role of cognition in this thesis is critical. A basic model is presented that outlines a framework to understand the cognitive factors affecting economic decision-making and their inter-relationship. The specific inclusion of perception, as a factor enabling the movement of financial stress from an exogenous 'shock' to effect short-term cognitive capacity, is an important contribution. The model also includes a specific heuristic - attribute non-attendance. The model identifies a pathway between financial stress, cognition, heuristic use and household expenditure. This basic model is expanded and empirically tested. Empirical analysis is supported by data collected in Samburu county, Kenya. The stressor used in this study was a severe and protracted drought between 2015 and 2017. Repeated measures are taken of rural respondents over a 10-month period as communities recovered from the drought. Controlling for household income, fluid intelligence and choice heuristic use are important channels affecting household expenditure decisions. The relative importance of perceptual scarcity, relative to resource scarcity, in affecting economic decision-making is also identified.

Introduction

The work of Mullainathan and Shafir (2013) has renewed emphasis on individual perceptions of economic scarcity as they affect decision-making. The authors distinguish between a traditional economic understanding of scarcity and unobservable perceptions of scarcity: '[S]carcity is not just a physical constraint. It is also a mindset. When scarcity captures our attention, it changes the way we think…' (2013, p. 12). While this scarcity thesis is supported by a range of examples - diets and busyness, in particular - it has a particular application to explaining poverty and why the global poor perform so badly across a wide range of behaviours (Mullainathan and Shafir, 2013, pp. 153-155). As a result, further consideration of the role of perceived scarcity on economic behaviours is warranted.

The current research aims to fill, if partially, some of these gaps in developing a model of the effects of financial stress on economic decision-making. Perception and heuristic use function as intermediaries transferring the effects of a stressor through cognition to affect economic decision-making. The proposed model is tested using repeated measures from rural Kenya as communities managed the stress of a prolonged and severe drought. Cognition is measured using fluid intelligence among a sample that is predominately illiterate and poor - in absolute and relative senses. Measurement of the use of an attribute trade-off heuristic mediates the effects of cognition on decision-making. While the socio-economic characteristics of the sample is not representative of populations in high income, the ability to control for level of schooling offers insights into the effect of schooling on cognition measurements.

Model

The present model (Figure 1) is general in form. It includes channels for direct and indirect effects. The initiating 'stressor' may represent one or more forms of stress. The inclusion of the discrete domain of perception/affect provides flexibility and realism by allowing for a separation of the stressor and its interpretation by the decision-maker. As individuals perceive a given stressor in different ways, so too will the responding effect on cognition differ. The definition of cognition is left open and is not restricted. This allows for differing cognitive mechanisms to be considered in differing decision contexts and among differing populations. Finally, the basic model presented above specifies the domain of heuristics functioning as an intermediary between cognition and economic decision-making. Adamkovič and Martončik propose an undefined "Intuitive style of thinking" or System 1 mechanism, as proposed by dual-process theory (2017). The implicit assumption here is that System 1 forms of cognitive processing are inherently negative. This appears as an over simplification of the outcomes of dual processing theory. Figure 1 includes feedback from economic decision-making to perceptions. This feedback is not tested in the present analysis due to the limited number of observation points.

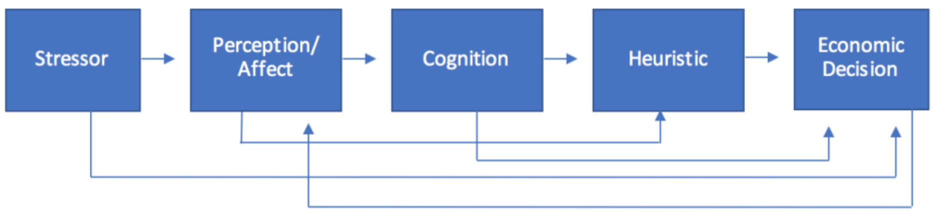

Figure 1: Basic model of cognition on economic decision-making.

Perception

The domain of perception and affect serves as a mechanism by which an exogenous stressor is mentally processed and interpreted. While affect has a clearly defined place in the experimental literature as it relates to poverty (Haushofer and Fehr, 2014), its place within a wider cognitive - decision framework is less clear. Drawing on the Gestalt tradition (Koehler, 1947), perceptual psychology acknowledges the close interplay between affect and cognition through the perceptual field (Glöckner and Betsch, 2008). Katona (1975) utilises positive backward and forward perceptions of financial well-being on household consumption. Accordingly, the perceptual field extends beyond the immediate physical environment. The meaning given to any physical, interpersonal or thought may take on different meanings for individuals who experience the same phenomenon due to differences in their perception. The construction and function of perception may well generate affect and influence behavior directly or, as the model allows, indirectly through changes in cognition.

Cognition and Cognitive Cost

Experimental data consistently indicates that cognitive capacity and heuristic use are strong predictors of performance on rational thinking tasks. Within a dual-processing framework, the predicted positive performance on the Cognitive Reflective Test, proposed by Kahneman and Frederick (2002), is causally related to positive cognitive capacity and negative heuristic use (Frederick, 2005; Toplak et al., 2011). The Cognitive Reflective Test measures one's tendency to override incorrect autonomous or immediate responses with extended reflection. The simultaneous channels of cognitive capacity (as measured by fluid intelligence) and mechanisms to simplify choices, as predictors of reflective thought, are also predictors of choices that have uncertain and delayed returns. While not tested in the current paper, changes in risk preferences are hypothesised related to changes in reflective thought (Shah et al., 2015; Burks et al., 2009; Dohmen et al., 2010).

Heuristics and Decision-Making

Heuristics appear as a natural intermediary connecting changes in cognition with market decisions. Higher levels of cognition or intelligence is negatively associated with use of representative, matching, and gain/loss heuristics (Kokis et al., 2002). Changes in how an individual values trade-offs and discounting over time are likely explanations for how heuristics may affect decision-making. However, testing the strength of this relationship in market contexts has not been a focus of psychology research. The mental strategy of reducing a commodity's relevant attributes is commonly acknowledged in economics to affect decision-making. Hensher (2006) introduced the concept in analysis of discrete choice experiments. The approach has strong resonance with theories of consumer demand proposed by Lancaster (1966) and is closely associated with the decision-making work of Gigerenzer and Goldstein (1996) as an intuitive strategy for reducing the cognitive load of a given decision. The role of heuristic use as an intermediary between cognition and decision-making is an explanation supported by the findings of Frederick (2005) and Shah et al. (2015). Reviews of the literature are available elsewhere (Adamkovič and Martončik, 2017; Haushofer and Fehr, 2014).

Methods and Material

Dynamic panel data analysis is used to test the plausibility of the basic model of cognition in economic decision-making. A maximum likelihood (ML) approach is used to estimate a linear dynamic panel-data estimator (Moral-Benito et al., 2019; Williams et al., 2018). This approach is in contrast to the more common GMM approach, which is employed by the Arellano-Bond (AB) estimators. Other ML approaches exist, but are infrequently applied (Hsiao et al., 2002; Moral-

Benito, 2013). The programming requirements make these approaches restrictive. The Arellano-Bond approach is not fully efficient, particularly when the autoregressive parameter approaches one (Ahn and Schmidt, 1995) or when the cross-sectional dimension of the panel is small (i.e. small N) (Moral-Benito et al., 2019).

The structure of the model is presented, in equation 1, using conventional econometric notation.

$$y_{it} = \lambda y_{it-1} + \mathbf{x}'_{it} + \alpha_i + \xi_t + \nu_{it}, \tag{1}$$

where $\mathbf{x}'_{it}$ is a vector is exogenous and predetermined time-varying variables. The unobserved fixed effect is captured by α_i and ξ_t reflects the unobserved factors common across the panel. The subscript *t* runs from 1 - 3. As a result, only one lag is permissible. In the same manner as the Arellano-Bond approach, the exogenous **x** variables function as instruments for the endogenous lagged y variable (Arellano, 2003). In first difference form, equation (1), without the subscript *i*, may be written as

$$y_3 - y_2 = \lambda(y_2 - y_1) + \beta_1(x_3 - x_2) + \beta_2(x_2 - x_1) + (\nu_3 - \upsilon_2). \tag{2}$$

The matrices for the covariance and coefficients are presented by Moral-Benito et al. (2019). Simulation results comparing the ML approach with that of the AB on balanced and unbalanced panels, shows that for samples of 200 and 500 the biasedness of estimates is consistently lower using the ML estimator (Moral-Benito et al., 2019). The ML approach uses a Full Information ML estimator when unbalanced panels are used.

A series of estimates are performed that assess the relationship between each domain outlined in Figure 1. Three sets of estimates are presented. The first uses a Generalized Estimating Equations (GEE) estimator to assess the relationship between the exogneous variables of the environmental stressor (Normalised Difference Vegetation Index -NDVI) and the binary perception measures (backward and forward-looking). A set of four estimates are presented - one backward and three forward. Equation (3) details the estimation. A second set of estimates has fluid intelligence as the dependent variable and progressively increases the number of independent variables. Equation (4) details the structure of the full model. The dynamic panel maximum likelihood estimators is used for these estimates. Two covariates (illiterate and female) that are fixed over each round are included. The use of the structural equation framework allows for the inclusion of time indifferent variables (Williams et al., 2018). The third set of estimates uses household expenditure, by category, as the dependent variable. Equation (5) details this set of models. The expenditure categories used are: livestock, crops and education.

$$Perception_{it} = \beta_0 + \beta_1 NDVI_{it} + e_{it} \tag{3}$$

$$Fluid\ intelligence_{it} = Fluid\ intelligence_{it-1} + Perception_{it} + NDVI_{it} + Nonpoor_{it} + Covariates_i + \nu_{it} \tag{4}$$

$$Expenditure_{it} = Expenditure_{it-1} + Heuristic_{it} + Fluid\ intelligence_{it} + Perception_{it} + NDVI_{it} + Nonpoor_{it} + Covariates_i + \nu_{it} \tag{5}$$

The selection of fluid intelligence as a measure of cognition is validated by prior studies and in comparison to Working Memory Capacity (WMC). Appendix A compares dynamic panel ML results using *gf* (fluid intelligence), WMC and Heuristic as the dependent variable and the other cognition variables as independent variables, along with perception measures, environmental stressor and covariates. A comparison between *gf* and WMC indicates that each measure is independent of the other and that the *gf* model is consistently affected by perceptions of financial well-being. Moreover, the goodness-of-fit of the *gf* model is considerably higher (0.83 vs 0.45).

Data was collected in agro-pastoralist communities of south-western Samburu county, Kenya. The principal town in the county is Maralal (approximately 300 km north of Nairobi). The stressor used in this study is a severe and protracted drought between 2015 and 2017. Samburu county received 10 out of 11 continuous quarters of below average rainfall prior to the commencement of the study. The proceeding seven quarters each had rainfall below the long-term average. Table 1 shows the difference in rainfall between actual and long-term average. Rounds 1 and 2 of data collection were timed to coincide with the two traditional rainy seasons: round 1 in early November 2017 and round 2 in early March. Round 3 occurred at the end of August and before the October-November rains. Given respondents' knowledge of average weather patterns, and the realities of the drought, the timing of data collection was aimed to capture natural variance in respondents' perceptions of the immediate future financial well-being of their household. The stress inducing effect of the drought is validated by the known physiological response of increased cortisol production (Chemin et al., 2013).

Table 1: Rainfall (mm) and survey rounds.

	2017								**2018**								
	Q2		**Q3**			**Q4**			**Q1**			**Q2**			**Q3**		
	May	June	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep
Rainfall	56	10	26	25	8	86	94	24	8	10	148	270	66	53	16	19	5
Diff (Rainfall - LTA)	-13	-38	-39	-39	-23	**41**	-20	-5	-7	-15	**110**	**172**	-3	**15**	-49	-45	-26

(Source: Government of Kenya, 2018)

(Round1) (Round 2) (Round3)

A total of 655 observations are used in this analysis. These observations represent observations over two consecutive rounds (i.e. respondents who only provided information in rounds 1 and 3 are excluded). A six-month interval is present between the second and third observations, while a four-month interval is present between the first and second observations. The exclusion of observations that are approximately 10 months apart helps to ensure that comparisons within the panel data are done over similar time periods. The data is unbalanced. Young males in rounds 2 and 3 were lost to follow-up. This was due to their role as herdsmen who drive and tend to cattle away from their respective villages. The Samburu are culturally associated with cattle and goat tending. Environmental conditions and their economic reliance on livestock dictate that the Samburu, along with other pastoralist communities in East Africa, are semi-nomadic (Liao 2018a,b).

Surveys took, on average, 45 minutes to complete. Prior to the first survey round, respondents were unaware that a gift of food (equivalent of $2.50) would be given to respondents. This gift acknowledged the time commitment required to complete the survey tools. It is not believed that the gift was a motivating factor for respondents to complete the survey. All respondents were also offered a basic lunch on the day they completed the survey. No explicit follow-up strategy was employed prior to round 2. Community leaders were tasked to call and remind respondents to attend the third round of data collection.

Table 2 presents summary statistics of relevant variables. The variable NDVI is a measure of vegetation coverage based on satellite imagery (Abatzoglou et al., 2018). The correlation between the 3-month mean difference between long-term average rainfall and actual rainfall and NDVI is -0.81. NDVI data is available at the village level. The backward-looking perception variable measured the extent to which "the financial experience of your household over the past three-months was worse than expected". A forward-looking perception variable - 'Forward' - measured "how do you rate the financial well-being of your household over the next 3-months?". A five point Likert scale was used to record responses that ranged from 'very bad' to 'very good'. The variables 'Forward_Bad'. 'Forward_Average' and 'Forward_Good' are binary variables based on 'bad and very bad', 'average' and 'good and very good' responses from the above Likert scale.

Table 2: Descriptive Statistics

	Full				Round 1				Round 2				Round 3			
	Obs	Mean	Min	Max	Obs	Mean	Min	Max	Obs	Mean	Min	Max	Obs	Mean	Min	Max
Stressor																
NDVI	650	134	114	164	221	125	115	133	277	131	121	140	152	154	133	164
Perception																
Backward	651	0.91	0	1	221	0.89	0	1	278	0.93	0	1	278	0.89	0	1
Forward1	655	0.03	0	1	221	0.05	0	1	282	0.03	0	1	152	0.01	0	1
Forward2	655	0.29	0	1	221	0.43	0	1	282	0.32	0	1	152	0.01	0	1
Forward3	655	0.64	0	1	221	0.51	0	1	282	0.65	0	1	282	0.65	0	1
Cognition																
RPM	649	5.73	0	13	221	4.74	0	12	276	6.37	0	13	152	6.01	1	13
ANA	650	6.71	0	18	221	7.53	0	18	277	5.75	0	18	152	7.27	1	18
Assets																
Nonpoor	655	0.17	0	1	221	0.19	0	1	282	0.21	0	1	152	0.07	0	1
Expenditure ('000s)																
Crops	648	0.79	0	8.8	221	0.89	0	8.8	277	0.74	0	6.3	150	0.74	0	6.3
Livestock	649	0.67	0	37.5	221	0.80	0	37.5	276	0.54	0	6.6	152	0.54	0	6.6
Edu.	650	2.18	0	18.8	221	2.40	0	18.8	277	2.31	0	15.0	152	1.62	0	18.8

Cognition is measured using fluid intelligence and choice heuristic. A short-form of the Standard Raven's Progressive Matrices (RPM) was used to measure fluid intelligence. The tool contained 20 items. The difficulty of these tasks mirrored the distribution of the difficulty in the full Standard RPM set of exercise (Foster et al., 2015). The mean score of 5.7 is present in the data across all rounds, with a low of zero (e.g. floor effect) and a maximum of 13. The correct answering of 29 percent of the items in this study equates well to the 21 and 29 percent of items correctly answered, using the full coloured RPM, in rural Kenya in 1984 and 1998 (Daley et al., 2003). With respect to the heuristic measurement, respondents nominated which, if any, attributes they ignored when making their choice in the discrete choice experiment (Iles et al., 2019). This heuristic mechanism is known as ‘Attribute Non-Attendance’ (Hensher, 2006). A maximum of three attributes across six tasks could be selected - totaling 18.

Changes in variables, and their respective directions, provides further insight into the nature of the data. Results from two sample t tests indicate that the mean changes in NDVI, fluid intelligence, heuristic use and perceptions of household financial well-being are captured across the three rounds of data collection. The increases in mean NDVI reflect the breaking of the drought during 2017 - 2018. The increasing mean NDVI are statistically different at the one percent level from rounds 1 and 2, and then between rounds 2 and 3 (using a one-tail test; t values of 12.1, 25.7). The mean RPM scores in rounds 1 (4.7) and 2 (6.4) are statistically different at the one percent level (using a one-tail test; t value of 6.8). In line with the increases in RPM scores between rounds 1 and 2, the ANA scores decreased from 7.5 in round 1 to 5.8 in round 2 (using a one-tail test; t value of 5.2). The movement of fluid intelligence and heuristic use in opposite directions is as expected. Increased cognitive capacity (i.e. higher RPM scores) is expected to enable a greater capacity to consider a wide set of attribute trade-offs (i.e. lower ANA score). No statistical difference is observed in RPM scores between rounds 2 and 3 (using a one-tail test; t value of 1.3). However, the mean ANA scores increase during this same period (using a one-tail test; t value of 3.9). The relative movements of fluid intelligence and heuristic use are not explained by differences in the sample represented in each round. The same movements are observed among respondents who answered all three rounds (n = 76 respondents; statistical differences are measured at the five percent level).

Changes in households’ perceptions of their financial well-being are observed among the measure of forward looking well-being. The proportion of households who rated their next 3-months being good or very good financially rose from 0.51 to 0.65 to 0.82. Each increase was statistically different from the previous (using a one-tail test; t values of 3.1 and 3.7). These forward-looking perceptions map closely with the improvements observed in aggregate environmental conditions over the same period. No statistical differences are observed using mean backward-looking perceptions of financial well-being.

Estimates of household income (two sources - livestock and crops) show no changes between rounds 1 and 2, but decrease between rounds 2 and 3. The variable ‘Nonpoor’ is set to 1 when household monthly income (per person) is above the Kenyan rural poverty line of KES 3230 (USD 31 - direct exchange and USD 1486 - purchasing power, 2016 level of 0.46). The combination of the lagged nature of crop and livestock income and the effects of a prolonged drought help explain this observed pattern. Although environmental conditions improve at each interval, improvements in household income were yet to be realised. The backward-looking perception of financial well-being should not be expected to closely mirror household income (per person) results. The relative measure of backward-looking perception (relative to prior expectations) controls for expectations. It may be easily assumed that households, experienced in living through droughts, would have built worsening income conditions, as the drought proceeded, into their expectations.

Household expenditure data is based on recall of expenditure over the past two weeks. In the case of crops and livestock, a three-month window is used due to the lumpiness of payments during the year. Mean expenditure on crops and livestock are highest at KES 793 and 676, respectively. Each of these categories have high standard deviations, reflecting in part seasonal and between household variations. Mean education expenditure is KES 2180 (USD 21).

Results

Coefficient estimates are presented in three groups. The first group estimates the relationship between stressors and perceptions of financial well-being. Models 2 and 3 in Table 3 demonstrate the predicted negative effect of increases in current NDVI on forward-looking perceptions. Model 4 shows that current NDVI had a positive effect on the likelihood of nominating that the immediate future will be good. Increases in current NDVI had no effect on respondents’ perceptions of their immediate past, relative to prior expectations.

Table 3:

	Model 1		Model 2		Model 3		Model 4	
Dependent (y)	Backward		Forward_Bad		Forward_Average		Forward_Good	
	Coeff.		Coeff.		Coeff.		Coeff.	
NDVI	-0.001		-0.018	*	-0.037	***	0.017	***
Constant	1.397	*	0.484		4.344	***	-1.892	***

GEE population average estimator, robust standard errors used.

Note: statistical significance is denoted by: * 0.05 level, ** 0.01 level, *** 0.001.

Across the three models in Table 4, fluid intelligence (*gf*) is the dependent variable. In Models 5, 6 and 7 the lagged fluid intelligence variable is statistically significant at the one percent level. The lagged coefficients are estimated between -0.40 and -0.42 across these models. The NDVI parameter estimates are not statistically significant in any of these models. The inclusion of backward-looking perceptions of financial well-being, in Models 6 and 7, is estimated to have a negative effect on fluid intelligence. Perceptions of good forward-looking well-being has no effect on fluid intelligence. Illiteracy has a strong effect on short-term changes in fluid intelligence. The parameter estimate for illiteracy in Model 7 is -1.95 and statistically significant at the 0.001 percent level.

Table 4:

	Model 5		Model 6		Model 7	
	Coeff.		Coeff.		Coeff.	
Lagged *gf*	-0.401	**	-0.423	***	-0.410	**
Backward	-		-1.135	*	-1.185	*
Forward_Good	-		-0.015		-0.006	
NDVI	0.001		0.008		0.005	
Heuristic (ANA)	-		-		0.009	
Nonpoor	-		-		0.239	
Illiterate	-		-		-1.953	***
Female	-		-		-0.110	
CD	0.814		0.842		0.836	
N	376		376		376	

Robust standard errors used.
Note: statistical significance is denoted by: * 0.05 level, ** 0.01 level, *** 0.001;
CD - Coefficient of Determination.

Models 8 through 10 estimate the effects of cognition, perceptions of financial well-being and covariates on household expenditure. The estimates in Table 5 include those for crops, livestock and education. Across each of these expenditure categories the heuristic parameter estimate is consistently negative and statistically significant. Other variables of explanatory power in Model 5 (crop expenditure) are: ‘good’ forward-looking perceptions, fluid intelligence, and illiteracy. ‘Good’ forward-looking perception has a positive parameter estimate of 387.3. Fluid intelligence and illiteracy both have negative parameter estimates: -83.2 and -295.2. The ‘Nonpoor’ parameter estimates in both Models 8 and 9 near statistical significance with p-values of 0.054.

Table 5:

	Model 8		**Model 9**		**Model 10**	
Dependent (y)	Crops		Livestock		Edu.	
	Coeff.		Coeff.		Coeff.	
Lagged y	-0.253		-0.273		0.106	
Backward	130.617		118.052		1505.317	
Forward_Good	387.290	**	119.085		436.114	
NDVI	-13.799		2.448		10.096	
Gf (RPM)	-83.234	**	15.484		-2.365	
Heuristic (ANA)	-65.756	***	-37.733	*	-118.015	**
Nonpoor	383.759		279.711		323.957	
Illiterate	-295.213	*	53.379		231.264	
Female	-112.423		-149.110		-647.129	*
CD	0.569		0.817		0.488	
N	376		376		376	

Robust standard errors used.

Note: statistical significance is denoted by: * 0.05 level, ** 0.01 level, *** 0.001; CD - Coefficient of Determination

Discussion

Results from Tables 3, 4 and 5 support the hypothesis that backward and forward-looking perceptions of household financial well-being affect short-term changes in cognition. Parameter estimates in Models 6 and 7 (Table 4) demonstrate the effect of negative backward-looking perceptions of financial well-being (relative to prior expectations) on fluid intelligence. The control of baseline fluid intelligence through the lagged variable enables a clear identification of the effect of backward-looking perceptions on short-term changes in fluid intelligence. An indirect effect of negative backward-looking perceptions is identified to affect crop expenditure. The negative fluid intelligence parameter estimate (Model 8) reflects the impact of negative backward-looking perceptions.

The direct effect of positive perceptions of future financial well-being on crop expenditure (Model 8) contrasts to the negative indirect effect of negative backward-looking perceptions. The positive effect of positive future financial well-being on crop expenditure makes intuitive sense. The positive effect of improving environmental conditions, through increasing NDVI, provides decision-makers with confidence that the worst of the drought is over and that crops planted have an improved chance of survival. Results from Table 3 indicate that decreases in environmental stress (i.e. improvements in NDVI) lowered the predicted probability of perceiving immediate future financial well-being in a negative or average manner. The same changes in NDVI had the opposite effect on predictions of perceived good future financial well-being.

Evidence from Table 5 indicates that short-term changes in fluid intelligence and use of choice heuristics is expected to affect household expenditure decisions. Heuristic use is a negative predictor for engagement in reflective thought (Frederick, 2005; Toplak et al., 2011). The dual processing interpretation of heuristic use provides an instructive lens through which to interpret heuristic use parameter estimates. The ANA parameter estimate has an estimated negative effect on all expenditure categories. Decreases in reflective thought is predicted to lower household expenditure in crops, livestock and education. These results do not indicate whether such reduced expenditure is optimal. The degree of choice that households experienced in these expenditure areas is unclear. However, knowledge of decision biases associated with future returns and the relative cognitive load of decisions in different domains provides guidance.

The results of the current study extend the scarcity thesis (Mullainathan and Shafir, 2013). Results from Table 4 identify that environmental stressors affect fluid intelligence capacity. Controlling for a lack of schooling is shown as an important covariate mediating the effect of changes in fluid intelligence. While the original scarcity thesis, articulated by Mullainathan and Shafir (2013), hypothesised that changes in cognitive capacity affected economic decision-making, it was not tested. Subsequent research has questioned the empirical basis of this hypothesis (Carvalho, et al., 2016). The results presented in Table 5 demonstrate that heuristic use (i.e. ANA) does affect selected domains of household economic decision-making.

The absence of a randomised control group means that the effects of uncontrolled factors cannot be ruled out. The absence of a comparator group not experiencing drought conditions limits our ability to discount the effects of unobserved factors. While this limitation is present, it is not uncommon and does not invalidate the reported results. The collection of data over one cycle of agricultural production (i.e. 10 months) limits any seasonal effects. Potential effects of malnutrition and mental health concerns are also discounted. The Samburu county government ran a food (i.e. maize flour) distribution programme (in partnership with USAID) during the drought (USAID, 2017). This programme limits the possible effect of malnutrition on cognitive results. A five-item version of the Warwick-Edinburgh Mental Health Well-Being survey was incorporated into the survey. Scores show no change over time and have no analytical impact on results (see Figure 2A).

Conclusion

The importance of cognitive scarcity, relative to resource scarcity, in affecting economic decision-making is confirmed. Fluid intelligence and choice heuristic use are important channels affecting household expenditure decisions. The importance of these cognitive channels exists while controlling for household income. However, these factors are not universally important across the three categories of household expenditure. Crop and livestock expenditure are susceptible to changes in cognitive capacity. Therefore, the results presented support the scarcity thesis and confirm its ability to explain economic decision-making among the global poor. However, they also reveal that the nature and context of decision-making are also important.

References

Abatzoglou, J. T., Dobrowski, S. Z., Parks, S. A., & Hegewisch, K. C. (2018). *Terraclimate, a high-resolution global dataset of monthly climate and climatic water balance from 1958-2015*.

Adamkovič, M., & Martončik, M. (2017). A Review of Consequences of Poverty on Economic Decision-Making: A Hypothesized Model of a Cognitive Mechanism. *Frontiers in Psychology, 8*, p 1784.

Ahn, S. C., & Schmidt, P. (1995). Efficient estimation of models for dynamic panel data. *Journal of Econometrics, 68*(1), pp. 5-27.

Arellano, M. (2003). *Panel data econometrics*: Oxford University Press.

Burks, S.V., Carpenter, J.P., Goette, L., Rustichini, A. (2009). Cognitive skills affect economic preferences, strategic behavior, and job attachment. *Proceedings of the National Academy of Sciences*, *106*(19):7745.

Carvalho, L. S., Meier, S., & Wang, S. W. (2016). Poverty and Economic Decision-Making: Evidence from Changes in Financial Resources at Payday. *American Economic Review, 106*(2), pp. 260-284. doi:doi: 10.1257/aer.20140481

Chemin, M., de Laat, J., & Haushofer, J. (2013). *Negative Rainfall Shocks Increase Levels of the Stress Hormone Cortisol Among Poor Farmers in Kenya*. SSRN. Retrieved from https://ssrn.com/abstract=2294171

Daley, T. C., Whaley, S. E., Sigman, M. D., Espinosa, M. P., & Neumann, C. (2003). IQ on the rise: The Flynn effect in rural Kenyan children. *Psychological Science, 14*(3), pp. 215-219.

Dalton, P. S., Nhung, N., & Rüschenpöhler, J. (2019). Worries of the poor: The impact of financial burden on the risk attitudes of micro-entrepreneurs. *Journal of Economic Psychology*, pp.102198. doi:https://doi.org/10.1016/j.joep.2019.102198

Dohmen T, Falk A, Huffman D, Sunde U. (2010). Are Risk Aversion and Impatience Related to Cognitive Ability? *American Economic Review, 100*(3):1238-60.

Foster, J., Shipstead, Z., Harrison, T., Hicks, K., Redick, T., & Engle, R. (2015). Shortened complex span tasks can reliably measure working memory capacity. *Memory & Cognition, 43*(2), pp. 226-236. doi:10.3758/s13421-014-0461-7

Frederick, S. (2005). Cognitive Reflection and Decision Making. [10.1257/089533005775196732]. *Journal of Economic Perspectives*, *19*(4), pp. 25-42.

Gigerenzer, G., & Goldstein, D. G. (1996). Reasoning the fast and frugal way: models of bounded rationality. *Psychological Review, 103*(4), p 650.

Glöckner, A., & Betsch, T. (2008). Modeling Option and Strategy Choices with Connectionist Networks: Towards an Integrative Model of Automatic and Deliberate Decision Making. *Judgment and Decision Making, vol.3*(3).

Government of Kenya. (2018). National Drought Management Authority. *Early Warning Reports.* Retrieved from http://www.ndma.go.ke/index.php/resource-center/early-warning-reports

Haushofer, J., & Fehr, E. (2014). On the psychology of poverty. [10.1126/science.1232491]. *Science, 344*(6186), p 862.

Hensher, D. A. (2006). How do respondents process stated choice experiments? Attribute consideration under varying information load. *Journal of Applied Econometrics, 21*(6), pp. 861-878. doi:10.1002/jae.877

Hsiao, C., Pesaran, M. H., & Tahmiscioglu, A. K. (2002). Maximum likelihood estimation of fixed effects dynamic panel data models covering short time periods. *Journal of Econometrics, vol.109*(1), pp.107-150.

Iles, R. A., Gatumu, H., Kagundu, S., & Draheim, C. (2019). Information sharing and willingness-to-pay for CBPP vaccine in rural Kenya. *Vaccine, vol.37*(12), pp.1659-1666. doi:https://doi.org/10.1016/j.vaccine.2019.01.072

Kahneman, D., & Frederick, S. (2002). Representativeness revisited: Attribute substitution in intuitive judgment. *Heuristics and biases: The psychology of intuitive judgment, vol.49*, pp.81.

Katona, G. (1975). *Psychological Economics* New York: Elsevier Scientific Publishing Company.

Kirchler, M., Andersson, D., Bonn, C., Johannesson, M., Sørensen, E. Ø., Stefan, M., . . . Västfjäll, D. (2017). The effect of fast and slow decisions on risk taking. *Journal of Risk and Uncertainty, vol.54*(1), pp.37-59. doi:10.1007/s11166-017-9252-4

Koehler, W. (1947). *Gestalt Psychology: An Introduction to New Concepts in Modern Psychology* New York: Liveright Publishing Corporation.

Kokis, J. V., Macpherson, R., Toplak, M. E., West, R. F., & Stanovich, K. E. (2002). Heuristic and analytic processing: Age trends and associations with cognitive ability and cognitive styles. *Journal of Experimental Child Psychology, 83*(1), pp. 26-52.

Lancaster, K. J. (1966). A new approach to consumer theory. *Journal of political economy, 74*(2), pp. 132-157.

Liao, C. (2018a). Quantifying multi-scale pastoral mobility: Developing a metrics system and using GPS-Tracking data for evaluation. *Journal of Arid Environments, vol.153*, pp.88-97. doi:https://doi.org/10.1016/j.jaridenv.2017.12.012

Liao, C. (2018b). Modeling Herding Decision Making in the Extensive Grazing System in Southern Ethiopia. *Annals of the American Association of Geographers, vol.108*(1), pp.260-276. doi:10.1080/24694452.2017.1328306

Mani, A., Mullainathan, S., Shafir, E., & Zhao, J. (2013). Poverty Impedes Cognitive Function. [10.1126/science.1238041]. *Science, 341*(6149), p 976. Retrieved from http://science.sciencemag.org/content/341/6149/976.abstract

Moral-Benito, E. (2013). Likelihood-based estimation of dynamic panels with predetermined regressors. *Journal of Business & Economic Statistics, vol.31*(4), pp.451-472.

Moral-Benito, E., Allison, P., & Williams, R. (2019). Dynamic panel data modelling using maximum likelihood: an alternative to Arellano-Bond. *Applied Economics, vol.51*(20), pp.2221-2232.

Mullainathan, S., & Shafir, E. (2013). *Scarcity: The True Cost of Not Having Enough.* New York: Penguin Books.

Raven, J. (2000). The Raven's Progressive Matrices: Change and Stability over Culture and Time. *Cognitive Psychology, 41*(1), pp. 1-48. doi:https://doi.org/10.1006/cogp.1999.0735

Shah, A. K., Shafir, E., & Mullainathan, S. (2015). Scarcity Frames Value. *Psychological Science, 26*(4), pp. 402-412. doi:10.1177/0956797614563958 Retrieved from https://doi.org/10.1177/0956797614563958

Toplak, M. E., West, R. F., & Stanovich, K. E. (2011). The Cognitive Reflection Test as a predictor of performance on heuristics-and-biases tasks. *Memory & Cognition, vol.39*(7), pp.1275. doi:10.3758/s13421-011-0104-1

USAID. (2017). Kenya's county governments take lead in food assistance: Combined donations promote local resources. Retrieved from https://www.usaid.gov/results-data/success-stories/'twinning'-lends-hand-help-kenya-county-governments-take-lead-providing

Williams, R., Allison, P. D., & Moral-Benito, E. (2018). Linear dynamic panel-data estimation using maximum likelihood and structural equation modeling. *The Stata Journal, 18*(2), pp. 293-326.