Life history psychology, culture change, and recovery from extrinsic household shocks among Ethiopian farmers

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Abstract

Changes in subsistence technology can alter human life history behaviors. Unpredictability associated with culture change, similar to extrinsic mortality, could influence life history trade-offs involving delay discounting, reward seeking and impulsivity. Impulsivity is predicted to enhance exploration of new environments as an elaboration of life history mechanisms coopted for culture change. Exploration may improve accuracy of environmental expectations accelerating recovery from shocks. This study compares effects of impulsivity measured using short-form Barrett Impulsivity Scales (BIS) on time to recovery from extrinsic shocks (household morbidity-mortality and crop-livestock loss) among Sidama traditional enset and transitional maize farmers in Southwest Ethiopia (N=186). Lack of “Self Regulation” (Hazard Ratio = 5.4, \( P = 0.003 \)) and “General Impulsivity” (Hazard Ratio = 3.9, \( P = 0.005 \)) were associated with faster recovery from negative shocks among transitional maize farmers, but not among traditional enset farmers. This finding suggests that impulsivity may lead to adaptive functioning in unpredictable environments characterized by rapid culture change in niche construction. Health costs commonly associated with impulsivity may be an artifact of surplus production in WEIRD populations that was absent or uncommon in human environments of evolutionary adaptation (EEA).
1. Introduction

One premise of evolutionary psychology is that the mind/brain was shaped by natural selection to solve recurrent problems in the environment of evolutionary adaptation ([EEA] Lewis, Al-Shawaf, Conroy-Beam, Asao & Buss, 2017; Tooby & Cosmides 1992). The dawn of human behavioral modernity about 50,000 years ago posed a new problem for adaptation – culture change (Klein 1995). Over the last 50,000 years, and especially in the last 15,000 years, cultures have transformed and diversified rapidly such that today the rate of change is extreme with new technology, social organization, and livelihoods emerging over decades rather than millennia or generations (Foley 1995). Long-term increases in cultural complexity appear to be driven by population growth and unpredictability interacting with evolved cognitive capacities (Fogarty, Wakano, Feldman, Aoki 2017). Similarly, population growth and selection pressures since the origin of agriculture suggest relatively recent EEAs (<10,000 years) for some human adaptations (Hawks, Wang, Cochran, Harpending, Moyzis 2007). Culture may facilitate rapid biological adaptation (Thompson, Kirby & Smith 2016). Rapid and extreme changes in cultural niches may have selected for psychological adaptations for culture change.

Here impulsivity (lack of self-regulation and the tendency to act without regard to consequences or plans) is proposed as a psychological adaptation for changing cultural niches. Impulsivity involves “the inability to make decisions and act in a manner consistent with one’s global goals and values” (Fujita 2011:352). Shared cultural models (or representations) provide...
people with environmental expectations and distal goals relevant to a particular niche (D’Andrade 1992). In changing environments old cultural representations could provide inaccurate expectations and inappropriate goals for new conditions. The hypothesis is that impulsive personality, elaborated from basic life history mechanisms, allows people to ignore or break with cultural models, goals, and values that no longer predict adaptive outcomes. Impulsivity may function to generate new environmental models through inductive inference when old expectations fail in “predictive processing” (Clark 2013). In changing environments, impulsive people may navigate new circumstances and achieve improved functioning sooner than others who cling to outdated goals and values. Analyses presented here indicate that in changing and less predictable environments impulsivity reduced time to recovery from extrinsic (unavoidable) household shocks.

1.1 Life History & Phenotypic Plasticity

Standard life history models posit that unpredictable or extrinsic mortality – risk of death that cannot be altered by allocation of effort to components of fitness – results in “fast life history” (FLH). If adaptively significant outcomes are not predictable based on allocation of effort, then the fitness enhancing solution is to maximize current reproduction, which reduces mortality exposure and increases fertility (compensating for stochastic variance [Winterhalder & Leslie 2002]), to beat the odds of fitness failure (Chisholm 1999). FLH strategies involve early maturation, high fertility, and psychological features including delay discounting and impulsivity that promote current rather than delayed reproduction (DelGuidice et al 2015). Recent psychometric models characterize personality aspects for slow or K life history (e.g. Dunkel, Kim & Papini, 2012; Dunkel, Nedlec & van der Lindien, in press; Figuerdo et al 2005; Manson 2017). In contrast, the present study focuses on the fast end of the life history spectrum.
Life history strategies can be genetically fixed or they can be developmentally sensitive to conditions in early life (Belsky & Pluess 2009; Ellis, Boyce, Belsky, Bakermans-Kranenburg, & van Ijzendoorn, 2011). “Extended plasticity” (the ability to adaptively alter the phenotype throughout the life course) has been proposed, but it is relatively understudied (Del Guidice & Belsky 2011; Fawcett & Frankehuis 2015; Kubinski, Chopik, & Grimm 2017; Lewis 2015).

Benefits of genetically fixed versus developmentally plastic strategies depend on the predictability of environments over the life course. When conditions in early life predict conditions in adulthood, then a developmental “switch” for life history strategies is adaptive; however, when early life does not predict adult conditions, then a genetically fixed strategy should be advantageous (Nettle, Frankenhuuis & Rickard, 2013). This conclusion assumes that mechanisms for life-history regulation respond in two time-scales: evolutionary and developmental. Human minds/brains have some ability to adapt to changing local conditions with mechanisms that operate over different time scales: genetic adaptation over evolutionary time; cultural adaptation over generations; developmental adaptations over the life course; and perception and cognition that can respond to immediate challenges (Sperber 1997; see Kuzawa & Bragg [2012] for a similar time-scale-adaptation scheme). Environmental uncertainty may increase short-term plasticity (DelGuidice & Belsky 2011; Frankenhuuis & Fraley 2017).

One key problem for human life history theory is that strategies are based on limited information where allocation of effort depends in part on cultural models of livelihood and local success. A change in subsistence technology that influences local carrying capacity can substantially alter reproductive value of trade-offs (Balidini 2015). Some life history models assume that FLH strategists are largely powerless in the face of uncertainty; they cannot alter the environment or their behavior in ways that reduce risk. All a fast strategist knows is that success
is unpredictable based on current cognitive/perceptual models of the environment. But how do people recognize a return to predictability after events that disrupted expectations (McElreath 2016)? Unpredictability due to environmental change could be reduced by exploring associations between new conditions and indicators of local success. Hence, impulsivity, delay discounting, reward seeking, and lack of self regulation might be evolved psychological responses that promote FLH (DelGuidice et al 2015; Frankenhuis, Panchanathan & Nettle 2016) and exploration informing new mental models of expected environments (see also Williams & Taylor 2006; Gören 2016). A large body of neuroscience research on perception and action suggests that Bayesian predictive processing is one promising possibility for human adaption to environmental change over short time scales (Clark 2013; Perreault, Moya & Boyd 2012; Pouget, Beck, Ma & Latham, 2013).

1.2 Bayesian Perception, Culture Shock & Impulsivity

People assesses the fit between mental models and environmental conditions through feedback from actions in context (Clark 2013). Repeated encounters with social, economic and biotic aspects of an environment shapes attention and expectations in “patterned practice” associated with cultural models or schema (Roepstorff et al 2010; Strauss and Quinn 1997). Experience in an environment shapes mental models which in turn provide “prior probabilities” for the outcomes of future actions (Clark 2013). People deploy this probabilistic or predictive mind in planning (Tousant 2009). Following action that produces unexpected results, the mind/brain adjusts the prior probabilities for plans in an attempt to reduce errors or “surprise” (Clark 2013; Friston, Kliner & Harrison, 2006; Friston et al 2015). Repeated failure to predict outcomes should lead to abandonment of perceptual models that fail to predict outcomes (Clark
When expectations conflict with incoming information, then a Bayesian mind can seek new input to reorganize perception to fit the changing environment. Response to “surprise” (failure of predictive perception) can be as simple as eye movements in search of useful information to adjust expectations (Friston, Adams, Perrinet, & Breakspear, 2012). In other cases, surprise might motivate a person to change position in the environment to better match perceptual schemata. People also probe the environment for new information to construct more accurate representations (Williams & Taylor 2006).

Culture provides people with socially transmitted environmental expectations and goals that are adaptively relevant for local history (Barkow 1989; Irons 1998). Cultural models of social exchange, for example, predict the outcome of encounters to some useful extent (e.g. Henrich et al 2010). In Bayesian terms (Pouget et al 2013; Tenenbaum, Kemp, Griffiths & Goodman, 2011), cultural models (received expectations) provide prior probabilities for achieving a goal. In reflexive processes – thinking about one’s self in imagined context – cultural models can inform strategic planning in cognitive “scenario building” related to the evolution of imagination (Alexander 1989; Bloch 2011). A person’s cognitive/perceptual state may resemble a conversation between predictive mental models and sensory information interacting to make sense of the world (Clark 2013; Friston 2005). Under stable conditions, socially transmitted plans should achieve culture-specific goals for locally defined success (Barkow 1989). Repeated environmental shocks, however, can make cultural models unreliable predictors of future outcomes (Quinlan et al 2016).

Theoretically, a poor fit between culturally encoded expectations and actual outcomes should produce FLH similar to extrinsic mortality (Quinlan 2017; Quinlan 2007) – mortality is
only one of many ways to fail. Empirical studies of “cultural consonance,” the extent to which culturally encoded expectations match individual experience (Dressler et al 2005, 2012, 2017), show that low consonance (poor fit) between expectations and experience predicts a suite of outcomes associated with costs of FLH. Low cultural consonance measured across gradients of environmental quality has been associated with reduced subjective well-being (Reyes Garcia et al 2010) depression (Dressler, Balieiro, Ribeiro & Dos Santos, 2007; Dressler, Balieiro, de Araujo, Sliva & Dos Santos, 2016), hypertension (Dressler, Borges, Balieiro & Dos Santos, 2005), substance use (Dressler, Ribeiro, Balieiro, Oths & Dos Santos, 2004; Reyes Garcia et al 2010), and inflammatory immune response (Dressler et al 2016; Dressler, Balieiro & Dos Santos, 2017) in small-scale (Tsimane’ [Reyes-Garcia et al 2010]) and large-scale populations (Dressler et al 2004). Cultural consonance has been shown to mediate the effects of socioeconomic status (SES), genetics, and early life adversity on depression, and this mediation was especially pronounced in lower SES communities (Dressler et al 2016). Chronic health effects may indicate “internal prediction” of future prospects (Hartman, Li, Nettle & Belsky 2017; Rickard, Frankenhuys & Nettle, 2014) similar to “weathering” in poor American communities (Geronimus 1992). These somatic effects provide feedback for life history strategies with less planning, delay discounting, early reproduction, etc. described in Pepper and Nettle’s “behavioral constellation of deprivation” (2017). Evidence linking cultural consonance to reproduction is lacking. However, a study comparing matrilocal Kashi and patrilocal Bengali showed that women in non-normative post-marital residence reproduced earlier than women who followed culture-specific residence norms (Leonetti & Nath 2009). Consonance as a measure of culturally encoded environmental expectations suggests that low consonance is associated with FLH strategies.
Other life history and personality research implies that adherence to cultural models influences adaptive trade-offs. Extroversion and Openness are “...thought to underlie exploration and proactive behaviors” related to fast life history strategies (de Vries, Tybur, Pollet & van Vugt 2016). “Openness to Experience” (McCrae & Costa 1997) yields mixed associations with life-history strategies; however, three Openness items related to received cultural models – “Favors conservative values in a variety of areas,” “Makes moral judgments,” “Is influenced by social pressures” – were positively associated with slow life history (Manson 2017). This finding suggests that in some contexts FLH involves rejection of established cultural norms. The basic five-factor personality structure, in fact, may be an artifact of complex cultural niches (Lukaszewski, Gurven, von Rueden & Schmitt 2017). What are some possible psychological responses for abandonment and reorganization of cultural models that no longer predict current conditions?

Impulsivity is characterized by lack of planning or premeditation, reduced self-regulation, delay discounting, and reward seeking (Morean et al 2014; Sharma et al. 2014; Stanford et al. 2009). Moeller et al. define impulsivity “as a predisposition toward rapid, unplanned reactions to internal or external stimuli without regard to the negative consequences of these reactions to the impulsive individuals or to others” (Moeller, Barratt, Dougherty, Schmitz, & Swann, 2001). Self-regulation presents “conflicts between two motives: one that presses for a smaller, more concrete and proximal reward, and the other that presses for a larger, more abstract and remote reward” (Fujita 2011:353). Here I propose that impulsivity has a cognitive/perceptual function in reducing predictive errors associated with outdated cultural expectations.

Mental models may be hierarchically organized where higher order models provide expectations, and lower order representations process input from the environment. Higher order
models (including cultural representations) develop through experience that provides Bayesian priors for making sense of the world (Clark 2013; Friston 2005). In Friston’s metaphor, mental models “gossip” between each other to arrive at accurate representations of the environment (Friston 2005). When lower order representations do not fit expectations from higher order representations, then higher order mental models can “tell” lower order models to “shut up” in an attempt to reduce error. However, ignoring information that is inconsistent with expectations can be maladaptive in new environments. When higher order models, including received cultural expectations, do not predict new outcomes, then impulsivity may be activated as a means of “shutting up” higher order models that produce inaccurate expectations. Thus, by ignoring culturally encoded “plans,” impulsivity may allow for development of new mental models that replace old and inaccurate representations. In terms of cognitive science, impulsivity may reduce the “cognitive penetration” of higher order cultural models and increase the learning rate in a new environment (see Hohwy 2017).

Impulsivity and delay discounting can be induced in experimental conditions by increasing cognitive load or noise (Deck & Jahedi 2015; Hinson, Jameson & Whitney, 2003; Koffarnus, Jarmolowicz, Mueller & Bickel, 2013). Cognitive load likely impedes useful probabilistic inference for the task at hand. Ecologically mismatched cultural models, common in poorer communities with substantial uncertainty, are one source of cognitive noise (see also Haushofer & Fehr 2014). When expectations fail, then a Bayesian mind may activate impulsivity to generate new input to reorganize perception for a new niche (Quinlan et al 2016). Reduced inhibition could yield more accurate perception of associations among novel events (Harnishfeger and Bjorklund 1994). Hence, impulsivity is a potential mechanism (or suite of mechanisms [Caswell, Bond, Duka & Morgan, 2015]) that reduces the influence of culturally
encoded plans and increases environmental input to restructure mental models for new environmental expectations. Behavioral activation and reward seeking components of impulsivity could be particularly useful in new environments (Carver and White 1994; Morean et al 2014).

Several studies indicate that impulsivity is differentially activated in response to hazards or shocks in stable versus unstable environments. Mortality cues differentially activated delay discounting for subjects from stable versus unstable environments in psychological experiments. Subjects from stable and unstable environments showed no differences in delay discounting in the absence of current mortality cues. However, subjects who grew up in relatively adverse environments showed increased delay discounting in response to a simple mortality cue while subjects from stable environments did not (Griskevicius, Tybur, Delton, & Robertson, 2011). Related experiments showed a similar pattern of results for expressed desire for current reproduction (Griskevicius, Delton, Robertson, & Tybur, 2011). Another study indicated a similar interaction effect between socioeconomic environment and recent uncertainty in shaping long or short-term time depth: Differences between time horizon for people from low and higher socioeconomic background only emerged when poorer subjects experienced recent uncertainty (Choi & Suh 2018). Economic experiments indicated that mean wealth levels did not influence delay discounting; however, negative income shocks resulted in increased delay discounting (Haushofer, Schunk, Fehr 2013). An observational study similarly indicated that Ethiopian farmers pursuing high-risk non-traditional maize production showed significant increase in impulsivity in response to household morbidity-mortality and negative income shocks compared with farmers in relatively stable environments cultivating traditional drought resistant crops. However, there was no difference in impulsivity for traditional and transitional farmers who did
not experience a recent shock (Quinlan et al 2016). Predictive processing based on recent experience may help explain these results.

The standard psychological assumption is that impulsivity is an indicator of poor mental health and a risk factor for multiple diseases (Bari & Robbins 2013; Chamorro et al 2012; Sharma, Markon & Clark, 2014; Stanford et al. 2009). Perceived pathological cognition, however, could promote adaptive behavior relevant to local conditions (Frankenhuis & deWeerth 2013), and distinctions between functional and dysfunctional impulsivity have been proposed (Dickman 1990). In a life history perspective, health consequences of impulsivity are costs of otherwise adaptive reproductive outcomes. In contrast, the hypothesis here is that in unpredictable environments characterized by rapid culture change, impulsivity leads to improved functioning, evident in enhanced subjective welfare and reduced time to recovery from shocks.

1.3 Sidama Subsistence Models & Hazards

The Sidama are a Cushitic-speaking people living between the Rift Valley lakes of Awassa and Abaya in southwestern Ethiopia (Hamer, 1987). Most Sidama live in the SNNPR (Southern Nations, Nationalities, and Peoples' Region), the most rural of the nine states in the Federal Democratic Republic of Ethiopia (CSAE 2013). Census estimates indicate three million Sidama, the fifth largest ethnic group in Ethiopia (CSAE 2013) in a country with more than 80 distinct ethnicities (Levine 2000). For more detailed descriptions of Sidama culture, history and ecology see Dira & Hewlett (2016); Quinlan, Quinlan & Dira (2014); Quinlan et al (2015); Quinlan et al (2016) and Kumo (2016).

The Sidama niche is partitioned into traditional enset and transitional maize farming. These niches involve well elaborated, easily expressed cognitive schema or “cultural theories” (sensu D’Andrade 1993) of agricultural production. Enset farming is a relatively stable closed
system with deep roots in time (Quinlan et al 2014): Livestock provide fertilizer for enset and milk for humans, enset provides fodder for cattle and starch for humans (Quinlan et al 2015). Enset is drought resistant and has a relatively low risk of crop loss, though recovery times are long when enset fails (Quinlan et al. 2015). Maize farming, recently introduced (circa 1950), is unstable and exposed to global shocks: Risk of crop loss is high given sensitivity to seasonal variation in rainfall. However, maize farms show better “engineering resilience” to crop loss (time to recovery [Hollings 1996]) than do enset farms (Quinlan et al. 2015).

Enset farming has a clear, time tested cultural model of production and diet (Quinlan et al 2014; 2015). Sidama people readily talk about this enset-livestock complex as a system. Indeed, traditional Sidama mine (house/yard) and gate (gardens) comprise compounds structured around enset production (Quinlan et al 2015). Above 1400m elevation with sufficient rainfall, the Sidama cultural theory of enset production performs as described by informants (Quinlan et al. 2015). Enset and waasa, the processed food it provides, are cherished commodities. However, Sidama report a decline in the predictability and amount of rainfall since the mid-1970’s. Enset does not provide adequate caloric returns in some areas where it previously thrived (Ibid.).

Maize, in contrast to enset, is a newcomer to Ethiopia and it was not widespread in SW Ethiopia until the mid-1970s (McCann 2001). In areas where a significant proportion of small-holders now grow maize, Sidama note that their parents hardly knew of it. In other Sidama districts, maize replaced enset as the primary crop (Quinlan et al. 2015). A cultural schema or theory of maize production is evident and includes use of chemical fertilizer that is sensitive to price fluctuations and global shocks distant from Sidama everyday life. During the late 1970s and ‘80s, in an attempt to address food insecurity and land shortage, the communist Derg regime subsidized maize production, providing hybrid seeds and fertilizer. “Neoliberalism” introduced
after the fall of the Derg regime in the 1990s, common throughout sub-Saharan Africa (Little 2014), left maize adopters more vulnerable to global fluctuations in prices for maize inputs and surplus sales. Although maize often provides large yields, it is sensitive to annual variations in rainfall. Maize farms have high crop loss rates, twice that of enset farms, but they recover quickly from shocks (Quinlan et al. 2015).

Sidama grow other crops for market; however, nearly all households reported either enset or maize as the primary crop (Quinlan et al 2015). Coffee and chat (a mild stimulant sometimes called khat in Kenya, Somalia and Yemen) are present in a small proportion of Sidama farms. Less than seven percent of the sample in Quinlan et al (2015, 2016) grew any coffee or chat. Very few Sidama (about 7%) indicated that they did any work for wages.

Farming in Ethiopia is high-risk. Nearly 40% of Sidama farmers report losing half or more their food crops in recent years, and crop loss leads to large deficits in per capita caloric production (Quinlan et al 2015). Here I examine Sidama farmers’ recovery (time to return to subjective pre-shock household wellbeing) as a function of psychological response to morbidity-mortality and negative economic shocks in traditional, lower risk enset production, and newer, high risk, market integrated, maize production. This analysis includes four Sidama communities representing a range of Sidama ecological and geographic variation: Traditional enset-dependent Arbegona in the Sidama highlands with < 3% of farms experiencing crop loss in the last seven years; mixed-crop Boricha and Lokka Abaya straddling mid- and low-lands with 47% and 51% of farms experience recent crop loss; and maize-dependent Hawassa Zuria with 57% of farms experiencing recent crop loss in the peri-urban zone of Hawassa city, the capital of SNNPRS. Few households produce surplus calories from crops and cattle. Mean (SD) per capita calories
per day from crops ranged from 441 (667) to 1151 (1827) for Sidama districts (Quinlan et al 2015). For more detailed site and sample descriptions see Quinlan et al. (2015, 2016).

In previous research in Sidama Zone, we used the Barratt Impulsiveness Scale (BIS) and exploratory factor analysis to develop two scales of impulsiveness for “Self Regulation” and “Impulsive Behavior” identified Morean et al (2014). We started with eight BIS items following Morean et al (2014) with 320 individuals reported in Quinlan et al (2016) including 186 people who experienced household shocks reported below. We set the minimum criteria for the scale as per Morean et al (2014) as follows: (1) Each item loaded ≥.5 on one factor; (2) Each factor had at least three items; and (3) cross-loadings were <.32. The eight-item factor solution using varimax rotation gave two factors (not shown) with two items loading less than <.5: “I concentrate easily” loaded at -.26 on the second factor, and “I act on impulse” loaded at .42 on the second factor. (Oblique rotation yielded similar results.) These two items did not substantially alter other factor loadings, although scales including these items showed lower reliability (Cronbach’s alpha). “I act on impulse” was a replacement for “I act on the spur of the moment” for which we could not develop an acceptable Sidama translation. “Act on impulse” and “act on the spur of the moment” come from same “packet” of BIS items (Ibid.). We removed the two items with low loadings and repeated the analysis yielding the factor solution in table 1 comparing Sidama factors with item loadings reported for a US population in Morean et al (2014). Cronbach’s alpha for items loading on Factor 1 was .68 and Factor 2 was .61. BIS items for Self Regulation and Impulsive Behavior were differentially associated with household shocks among transitional Sidama maize farmers, who increased impulsivity in response to shocks, and transitional enset farmers who did not (Quinlan et al 2016).
Table 1. Factors for Sidama Impulsiveness compared with a US sample (Quinlan et al 2016)

<table>
<thead>
<tr>
<th>Item</th>
<th>Factor 1</th>
<th>Factor 2</th>
<th>*Self Regulation</th>
<th>*Impulsive Behavior</th>
</tr>
</thead>
<tbody>
<tr>
<td>I plan tasks carefully</td>
<td>0.65</td>
<td>-0.22</td>
<td>0.62</td>
<td></td>
</tr>
<tr>
<td>I am self-controlled</td>
<td>0.60</td>
<td>-0.12</td>
<td>0.66</td>
<td></td>
</tr>
<tr>
<td>I am a careful thinker</td>
<td>0.53</td>
<td>-0.12</td>
<td>0.65</td>
<td>0.54</td>
</tr>
<tr>
<td>I say things without thinking</td>
<td>-0.15</td>
<td>0.57</td>
<td>0.54</td>
<td></td>
</tr>
<tr>
<td>I do things without thinking</td>
<td>-0.12</td>
<td>0.54</td>
<td>0.73</td>
<td>0.53</td>
</tr>
<tr>
<td>I don't &quot;pay attention&quot;</td>
<td>-0.30</td>
<td>0.51</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: *indicates factor loadings reported for US “CTNA” data in Morean et al (2014).

2. Methods

Quantitative data were collected by oral self-report questionnaires concerning household demography, morbidity-mortality, economic shocks, health, impulsivity and production as part of a pilot study of household resilience. The instrument included over 200 items covering topics for comparison with other social and economic studies in Africa. The research protocol was reviewed and approved by Washington State University Institutional Review Board for Human Subjects Research, and Sidama Zone Administration. Interviewers were five native Sidama, trilingual (Sidama, Amharic, & English), research assistants—four with university degrees, and three with prior survey research experience. The instrument was translated and back-translated from English to Amharic to English. The research assistants initially received the instrument in English and Amharic, then research assistants and senior personnel developed appropriate Sidama translations together. The final Sidama translation was back-translated orally in a focus group including all Sidama research assistants and Native English speaking and Native Sidama speaking senior researchers. Senior personnel field-tested the Sidama language instrument in teams of two including one Native English speaker and one Native Sidama speaker. Then, Sidama research assistants received one week of training in instrument administration. During the first week of data collection, Sidama assistants worked in teams of two supervised by senior
personnel to ensure uniformity in instrument administration. Subsequent quality control checks indicated that one interviewer had substantial difficulty with psychological portions of the interview. Otherwise, interviewer effects reported in Quinlan et al (2016) were not significant in analyses reported below.

Selecting an impulsivity scale required close attention to linguistic properties of the instrument, number of items, and the cultural relevance of impulsiveness items. Prior pilot research on personality measures indicated that the Barratt Impulsiveness Short Scale (BIS 15) (Spinella 2007) was a good mix of language with simple grammatical structures, relatively few culture-bound items (questions about skydiving, or driving fast), and a well-documented short scale for inclusion in a longer instrument without substantially contributing to informant fatigue. In general, the BIS shows convergent validity in neuroimaging studies of impulsiveness in clinical populations and reliability and validity that is useful in normative populations (Spinella 2007). However, the BIS-15 required modification for a subsistence population with low literacy rates (about half of this sample was illiterate, table 2, and 67% did not complete primary school). Modifications included removing items referring to attention in a “lecture” setting, and one item about “complex problems” that proved difficult to translate. Present analyses used unidimensional and two-factor solutions for BIS items in table 1. The unidimensional scale yielded Cronbach’s alpha=0.69. Unidimensional loadings were as follows: (1) I plan tasks carefully (0.64); (2) I am self-controlled (0.54); (3) I am a careful thinker (0.49); (4) I say things without thinking (-0.48); (5) I do things without thinking (-0.43); (6) I don’t pay attention (-0.56). The unidimensional scale was reverse-coded so that positive associations reported here indicate effects of impulsivity.
Does the BIS measure a trait or state? Response to culture change proposed here requires context-dependent personality variability. Impulsivity factors for motor- and self-control, including short-form BIS items, show 1-month test-retest reliabilities (Spearman’s r) of 0.67 for motor and 0.73 for self-control (Stanford et al. 2009:387). Baseline scores account for about 45%–53% of variance in scores one month later. Considering likely environmental continuity over one month, I conclude that impulsivity is a state (Quinlan et al 2016) with potential for developmental input and heritability of sensitivity to cues (Belsky & Pluess 2009).

Colleagues and I created a judgment sample of four districts/woreda discussed above (Quinlan et al 2015, 2016). Each Sidama assistant was randomly assigned a different kebele (neighborhood) within the district. Within the kebele assistants obtained a convenience sample, recruiting participants as they encountered adults while walking main neighborhood footpaths. We set a target sample size of 100 for each district. When we reached that target, we moved on to the next woreda. This sampling strategy was intended to balance representative sampling and research efficiency. Random sampling of households would have dramatically increased research time and expense beyond our budget constraints. These analyses were not intended as precise population estimates; however, the data are suitable for examining predicted associations.
Table 2. Descriptive Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>SD</th>
<th>Min</th>
<th>Max</th>
<th>Scale</th>
</tr>
</thead>
<tbody>
<tr>
<td>Recovery*</td>
<td>0.16</td>
<td>0.37</td>
<td>0</td>
<td>1</td>
<td>dichotomous</td>
</tr>
<tr>
<td>Time waiting for recovery**</td>
<td>3.24</td>
<td>2.07</td>
<td>1</td>
<td>8</td>
<td>years</td>
</tr>
<tr>
<td>Morbidity-mortality</td>
<td>0.42</td>
<td>0.50</td>
<td>0</td>
<td>1</td>
<td>dichotomous</td>
</tr>
<tr>
<td>Crop loss</td>
<td>0.45</td>
<td>0.50</td>
<td>0</td>
<td>1</td>
<td>dichotomous</td>
</tr>
<tr>
<td>Livestock loss</td>
<td>0.11</td>
<td>0.32</td>
<td>0</td>
<td>1</td>
<td>dichotomous</td>
</tr>
<tr>
<td>Proportion maize produced</td>
<td>0.41</td>
<td>0.41</td>
<td>0</td>
<td>1</td>
<td>proportion</td>
</tr>
<tr>
<td>Impulsivity (BIS one factor)</td>
<td>0.13</td>
<td>0.87</td>
<td>-1.20</td>
<td>2.25</td>
<td>z-score</td>
</tr>
<tr>
<td>Lack of Self Regulation</td>
<td>0.14</td>
<td>1.08</td>
<td>-1.54</td>
<td>2.32</td>
<td>z-score</td>
</tr>
<tr>
<td>Impulsive Behaviour</td>
<td>0.11</td>
<td>1.07</td>
<td>-1.37</td>
<td>2.56</td>
<td>z-score</td>
</tr>
<tr>
<td>Cattle</td>
<td>2.58</td>
<td>3.93</td>
<td>0</td>
<td>37</td>
<td>count</td>
</tr>
<tr>
<td>Kg of crops</td>
<td>472.74</td>
<td>840.07</td>
<td>0.5</td>
<td>10000</td>
<td>continuous</td>
</tr>
<tr>
<td>N Children in HH</td>
<td>3.91</td>
<td>2.45</td>
<td>0</td>
<td>11</td>
<td>count</td>
</tr>
<tr>
<td>N Adults in HH</td>
<td>1.99</td>
<td>2.59</td>
<td>0</td>
<td>17</td>
<td>count</td>
</tr>
<tr>
<td>Age</td>
<td>38.30</td>
<td>15.00</td>
<td>12</td>
<td>84</td>
<td>years</td>
</tr>
<tr>
<td>Gender (man=1, woman=0)</td>
<td>0.62</td>
<td>0.49</td>
<td>0</td>
<td>1</td>
<td>dichotomous</td>
</tr>
<tr>
<td>Literate (yes=1, no=0)</td>
<td>0.53</td>
<td>0.50</td>
<td>0</td>
<td>1</td>
<td>dichotomous</td>
</tr>
<tr>
<td>Arbegona District</td>
<td>0.15</td>
<td>0.35</td>
<td>0</td>
<td>1</td>
<td>dichotomous</td>
</tr>
<tr>
<td>Boricha District</td>
<td>0.26</td>
<td>0.44</td>
<td>0</td>
<td>1</td>
<td>dichotomous</td>
</tr>
<tr>
<td>Lokka Abaya District</td>
<td>0.27</td>
<td>0.45</td>
<td>0</td>
<td>1</td>
<td>dichotomous</td>
</tr>
<tr>
<td>Hawassa Zuria District</td>
<td>0.32</td>
<td>0.47</td>
<td>0</td>
<td>1</td>
<td>dichotomous</td>
</tr>
</tbody>
</table>

Notes: N=186; *Self-report variable indicating whether the household was worse, the same or better than before the shock. **Includes households still waiting to recover for hazards analysis. HH is household and indicates adults in addition to the informant. Data are not clustered by HH, i.e. each informant represents a unique household.

Cox regression for proportional hazards, used here, focuses on effects of impulsiveness on time to recovery from shocks in the context of new, high-risk versus traditional, low-risk production. Cox regression produces “hazard ratios” (HR), similar odds ratios in logistic regression, indicating the instantaneous probability of recovery from a shock: HR >1 indicates faster recovery, HR <1 indicates slower recovery. Cox regression allows for inclusion of censored cases, i.e., individuals still waiting to recover from the most recent shock. Recovery from shocks was assessed using simple self-report of whether households were worse, the same, or better off than before the reported shock. Self-report of the household as better off or same as
before the shock were coded as 1=recovered versus 0=worse (see Table 2) because (1) the objective was to assess recovery, and (2) a three-level outcome substantially complicates analysis and precludes hazards analysis. Two separate analyses examine three measures of impulsiveness: Self Regulation and Impulsive Behavior from the short-form BIS (Morean et al 2014), and an unidimensional solution including all six measures in table 1 (Cronbach’s alpha=0.69). Self Regulation items were reverse coded to indicate effects of “Lack of Self Regulation” on recovery from shocks. Economic shocks are loss of half or more of crops or death of livestock, and morbidity-mortality is death or serious illness (could not work for three months or more) of a household member. Informants were asked whether they had experienced crop-livestock loss or morbidity-mortality in the last five years. Informants who indicated a household shock were asked to recall the year of the shock (some reported shocks more than five years in the past indicated in table 2). Household shocks were pooled for these analyses for three reasons: (1) I had no basis for predicting different outcomes for morbidity-mortality and economic shocks; (2) >90% of shocks in one district with low crop loss were from morbidity-mortality; and (3) multiple dichotomous variables in multivariate hazards analyses reduces the expected cell count which can artificially increase hazards ratios. Alternate subsistence regimes are indicated by the proportion of maize from total crop production in the last year indicating engagement in a new subsistence technology (table 2). Kilograms of crops produced, and cattle are the main and most reliable indicators of Sidama income and assets, which may alter the effects impulsivity on time to recovery from shocks. Number of adults and children in the household could also affect time to recovery as a function of the balance of household dependents and producers, and they are included in subsequent models. Age, literacy and gender entered models as additional controls as they may affect household production and Impulsivity.
Modeling proceeded in three steps: The first step examines the most parsimonious (smallest) theoretical model including production system and impulsivity interactions. Impulsivity and maize production were centered around their means and the product indicated the interaction. The Impulsivity main effect was decentered (lowest value added to the centered factor score). The second step includes household characteristics (income, assets, and household composition) in attempt to “dislodge” effects of Impulsivity in the most parsimonious model. The third model adds individual characteristics (age, gender and literacy). I used multi-level hazards models in STATA 14 (mestreg) to control for clustering of observations by community (table 2). The proportional hazards assumption was tested with time-dependent covariates: none were significant ($P>0.05$) and they were excluded from models presented below.

3. Results

There were 320 households in the original sample (Quinlan et al 2016) of which 186 experienced a recent household shock included in hazards analyses here. Descriptive statistics are given in Table 2. Only 16% of households reported recovery from the most recent shock. Crop loss and morbidity-mortality were the most common recent shocks followed by livestock death. Distribution of the sample across four districts (table 2) reflects low crop loss risk in Arbegona (Quinlan et al 2015). Ninety-one percent of shocks in Arbegona were due to morbidity-mortality (not shown). Sixty-two percent of respondents were men. Fifty-three percent of the sample were literate.

The prediction is that impulsivity leads to shorter time to recovery from shocks in the newer maize dependent production system compared with traditional enset production, which is indicated by interaction (product) terms for production system (proportion of maize produced) and Impulsivity. A model including only the main effects for Impulsivity and maize production
gave non-significant results for Impulsivity (HR=0.94 ; \( P =0.77 \)) and maize production (HR=1.53; \( P =0.36 \)). Model 1 indicates, however, that Maize X Impulsivity was associated with substantially reduced time to recovery (Table 3 all models, Figure 1). One unit of increase in Impulsivity among maize farmers was associated with recovery 3.9 to 4.7 times as fast as people of average Impulsivity. The main effect of Impulsivity was not significant (table 3). Larger models including controls for income, assets, and individual characteristics did not dislodge the effect of Maize X Impulsivity on time to recovery (Table 3, Models 2 & 3). Information criteria (AIC and BIC) indicated that model 1 (table 3) was the best fit. AIC and BIC indicated a best fit post hoc model including Adults in the Household (Table 4). District effects indicated by constant and residual variance in tables 3-5 were minimal, nor did including district indicators in the individual level model appreciably alter results reported.

Using a two-factor solution for BIS items in table 1 gave similar results (Table 5). The interaction for Maize X Self-Regulation showed a hazard ratio >5 indicating one unit of increase in Lack of Self-Regulation for 100% maize production was associated with over 400% greater probability of “instantaneous” recovery from morbidity-mortality and negative income shocks. None of the control variables in Table 3 dislodged or substantially mediated the association between Maize X Self-Regulation and recovery. Impulsive Behavior (BIS factor 2, table 1) was not a significant predictor of recovery (table 5).
Table 3. Multivariate hazards models showing effects of Impulsivity on time to recovery from household shocks.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Model 1</th>
<th></th>
<th></th>
<th></th>
<th>Model 2</th>
<th></th>
<th></th>
<th></th>
<th>Model 3</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>HR</td>
<td>SE</td>
<td>P</td>
<td>95% CI</td>
<td>HR</td>
<td>SE</td>
<td>P</td>
<td>95% CI</td>
<td>HR</td>
<td>SE</td>
<td>P</td>
<td>95% CI</td>
</tr>
<tr>
<td>Constant</td>
<td>0.05</td>
<td>0.02</td>
<td>0.000</td>
<td>0.03 0.10</td>
<td>0.04</td>
<td>0.02</td>
<td>0.000</td>
<td>0.02 0.11</td>
<td>0.02</td>
<td>0.01</td>
<td>0.000</td>
<td>0.00 0.08</td>
</tr>
<tr>
<td>Proportion maize produced</td>
<td>1.03</td>
<td>0.54</td>
<td>0.953</td>
<td>0.37 2.85</td>
<td>0.80</td>
<td>0.44</td>
<td>0.683</td>
<td>0.27 2.35</td>
<td>0.82</td>
<td>0.46</td>
<td>0.723</td>
<td>0.28 2.44</td>
</tr>
<tr>
<td>Impulsivity (BIS one factor)</td>
<td>0.87</td>
<td>0.20</td>
<td>0.532</td>
<td>0.55 1.36</td>
<td>0.98</td>
<td>0.24</td>
<td>0.941</td>
<td>0.60 1.60</td>
<td>0.94</td>
<td>0.24</td>
<td>0.807</td>
<td>0.57 1.55</td>
</tr>
<tr>
<td>Maize X Impulsivity</td>
<td><strong>3.91</strong></td>
<td><strong>1.88</strong></td>
<td><strong>0.005</strong></td>
<td><strong>1.52</strong> 10.04</td>
<td><strong>4.53</strong></td>
<td><strong>2.28</strong></td>
<td><strong>0.003</strong></td>
<td><strong>1.69</strong> 12.14</td>
<td><strong>4.72</strong></td>
<td><strong>2.38</strong></td>
<td><strong>0.002</strong></td>
<td><strong>1.76</strong> 12.70</td>
</tr>
<tr>
<td>Cattle</td>
<td>1.05</td>
<td>0.04</td>
<td>0.233</td>
<td>0.97 1.14</td>
<td>1.05</td>
<td>0.04</td>
<td>0.213</td>
<td>0.97 1.14</td>
<td>1.05</td>
<td>0.04</td>
<td>0.213</td>
<td>0.97 1.14</td>
</tr>
<tr>
<td>Kg of crops</td>
<td>1.00</td>
<td>0.00</td>
<td>0.986</td>
<td>1.00 1.00</td>
<td>1.00</td>
<td>0.00</td>
<td>0.993</td>
<td>1.00 1.00</td>
<td>1.00</td>
<td>0.00</td>
<td>0.993</td>
<td>1.00 1.00</td>
</tr>
<tr>
<td>N Children in HH</td>
<td>0.94</td>
<td>0.08</td>
<td>0.482</td>
<td>0.79 1.12</td>
<td>0.94</td>
<td>0.09</td>
<td>0.544</td>
<td>0.78 1.14</td>
<td>0.94</td>
<td>0.09</td>
<td>0.544</td>
<td>0.78 1.14</td>
</tr>
<tr>
<td>N Adults in HH</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td><strong>1.11</strong></td>
<td><strong>0.05</strong></td>
<td><strong>0.020</strong></td>
<td><strong>1.02</strong> 1.22</td>
<td>1.09</td>
<td>0.06</td>
<td>0.090</td>
<td>0.99 1.21</td>
</tr>
<tr>
<td>Age</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1.02</td>
<td>0.01</td>
<td>0.122</td>
<td>0.99 1.05</td>
<td>1.02</td>
<td>0.01</td>
<td>0.122</td>
<td>0.99 1.05</td>
</tr>
<tr>
<td>Gender (man=1, woman=0)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.84</td>
<td>0.40</td>
<td>0.714</td>
<td>0.33 2.13</td>
<td>0.84</td>
<td>0.40</td>
<td>0.714</td>
<td>0.33 2.13</td>
</tr>
<tr>
<td>Literate (yes=1, no=0)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1.71</td>
<td>0.83</td>
<td>0.268</td>
<td>0.66 4.42</td>
<td>1.71</td>
<td>0.83</td>
<td>0.268</td>
<td>0.66 4.42</td>
</tr>
</tbody>
</table>

Note: HR is the adjusted Hazard Ratio for each variable; SE is the standard error of HR; P is the P-value for HR; 95% CI is the confidence interval; HH is household.
Table 4. Best fit multivariate hazards models showing effects of Impulsivity on time to recovery from household shocks.

<table>
<thead>
<tr>
<th></th>
<th>HR</th>
<th>SE</th>
<th>P</th>
<th>95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.04</td>
<td>0.01</td>
<td>0.000</td>
<td>0.02 0.08</td>
</tr>
<tr>
<td>Proportion maize produced</td>
<td>0.80</td>
<td>0.43</td>
<td>0.683</td>
<td>0.28 2.32</td>
</tr>
<tr>
<td>Impulsivity (BIS one factor)</td>
<td>0.96</td>
<td>0.23</td>
<td>0.872</td>
<td>0.60 1.54</td>
</tr>
<tr>
<td>Maize X Impulsivity</td>
<td>4.29</td>
<td>2.09</td>
<td>0.003</td>
<td>1.65 11.13</td>
</tr>
<tr>
<td>N Adults in HH</td>
<td>1.13</td>
<td>0.05</td>
<td>0.007</td>
<td>1.03 1.23</td>
</tr>
</tbody>
</table>

N adults in HH | 186
Wald chi-square | 16.12
Log Likelihood | -112.7
Model P-value | 0.0029
AIC | 235.5
BIC | 251.6
Variance (constant) | 7E-32
Variance (residual) | 2E-16
N of groups (woreda-district) | 4

Note: HR is the adjusted Hazard Ratio for each variable; SE is the standard error of HR; P is the P-value for HR; 95% CI is the confidence interval; HH is household.

Table 5. Multivariate hazards model of time to recovery using two factor BIS solution

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th></th>
<th></th>
<th>Model 2</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>HR</td>
<td>SE</td>
<td>P</td>
<td>95% CI</td>
<td>HR</td>
<td>SE</td>
</tr>
<tr>
<td>Constant</td>
<td>0.16</td>
<td>0.11</td>
<td>0.010</td>
<td>0.04 0.65</td>
<td>0.16</td>
<td>0.11</td>
</tr>
<tr>
<td>Proportion maize produced</td>
<td>0.54</td>
<td>0.36</td>
<td>0.350</td>
<td>0.14 1.99</td>
<td>0.52</td>
<td>0.33</td>
</tr>
<tr>
<td>Lack of Self Regulation z</td>
<td>1.40</td>
<td>0.33</td>
<td>0.156</td>
<td>0.88 2.22</td>
<td>1.40</td>
<td>0.33</td>
</tr>
<tr>
<td>Impulsive Behavior z</td>
<td>0.69</td>
<td>0.14</td>
<td>0.068</td>
<td>0.47 1.03</td>
<td>0.70</td>
<td>0.14</td>
</tr>
<tr>
<td>Maize X Self Regulation</td>
<td>5.24</td>
<td>2.94</td>
<td>0.003</td>
<td>1.74 15.76</td>
<td>5.42</td>
<td>2.67</td>
</tr>
<tr>
<td>Maize X Imp. Behavior</td>
<td>1.06</td>
<td>0.47</td>
<td>0.901</td>
<td>0.44 2.54</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

N | 186
Wald chi-square | 15.82
Log Likelihood | -111.8
Model P-value | 0.0074
AIC | 235.6
BIC | 255.0
Variance (constant) | 10E-34
Variance (residual) | 7E-18
N of groups (woreda-district) | 4

Note: HR is the adjusted Hazard Ratio for each variable; SE is the standard error of HR; P is the P-value for HR; 95% CI is the confidence interval; HH is household.
Figure 1. Predicted probability of recovery from separate logit models for levels of maize production characterizing the interaction effect in Table 3, Model 1. >50% Maize OR = 2.40, \( P = 0.021 \); <50% Maize OR = 0.63, \( P = 0.175 \).

4. Discussion

Impulsivity was associated with faster recovery from shocks among transitional maize farmers but not traditional enset farmers. A two-factor model yielded similar results for Lack of Self-Regulation; however, factor 2 (Impulsive Behavior) did not significantly interact with maize production nor was the main effect significant. There are several important limitations to this analysis, and alternative interpretations are possible.

4.1 Limitations and Alternative Interpretations

The recovery variable is a simple self-report, dichotomous measure of general household “welfare” in cross-sectional analysis. Better measures of household and individual condition across multiple domains and over time could improve inferences from similar analyses. The
present results, however, suggest a role for impulsivity in recovery from shocks in populations undergoing extensive culture change.

Additional measures of exploratory psychology among FLH strategists may prove useful (see de Vries *et al.* 2016). Extroversion, Openness, Reward Seeking, Delay Discounting, and Lack of Premeditation are personality factors relevant to exploration of new environments, and they are relatively easy to measure. However, linguistic structure of NEO-PRI items for example (Costa & McCrea 1992) inhibit translation for cross-cultural comparison, and less culture-bound instruments would be helpful. Future research should include larger samples and a diverse array of impulsivity measures. Reward Seeking, especially, is likely to be an important psychological process for life history in new environments. Short-scales using simple language, like the BIS/BAS which includes Reward Seeking (Carver & White 1994; Morean *et al.* 2014) are likely to be especially useful for research in small-scale, subsistence populations.

Lack of Self Regulation may approximate functional impulsivity, while Impulsive Behavior corresponds to dysfunctional impulsivity. BIS Impulsive Behavior items (Factor 2, Table 1 & Morean *et al.* 2014) correspond most closely with Dickman’s (1990) dysfunctional factor; however, items similar to BIS Self Regulation appear in both functional and dysfunctional factors (pp.97-98). Alternatively, a two-factor solution for Self Regulation and Impulsive Behavior could be an artifact of the scaling rules employed in Morean *et al.* (2014) followed in Quinlan *et al.* (2016). A single factor solution for the six BIS items in Table 1 yielded loadings for three items <0.50 (0.43 to 0.49) (Cronbach’s alpha=0.69), which would be cause for exclusion or rotation in Morean *et al.* (2014).

Alternative interpretations of the direction of causality are possible. Impulsive people may be more likely to pursue maize agriculture and report recovery when their material
condition is no different from less impulsive people. Similarly, other personality traits, such as Agreeableness, may make some people likely to report recovery sooner than less agreeable people. Peer assessments, better controls for other personality factors, and longitudinal design may offer more conclusive results.

4.2 Fast Life History & Cultural Niche Construction

Recent life history and fertility analyses converge on local (family, neighborhood, village) effects related to local cultural models of production and social organization (Lawson et al 2015; Streeter & Sear 2017; Stromer & Lumma 2014; Uggla & Mace 2015). Evolutionary demographers emphasize the need for psychological and cultural frameworks relevant to demographic transitions (e.g. Mattison & Sear 2016; Ross et al 2016; Sear, Lawson, Kaplan & Shenk, 2016; Stulp, Sear & Barret, 2016; Gibson 2014). Here the focus is on psychological processes for life history trade-offs and culture change.

Psychological processes for fast life history may have niche construction functions that promote environmental exploration (de Vries et al. 2016; Laland, Odling-Smee & Feldman, 2000). One key adaptive problem in rapidly changing environments is the ability to reach a new cultural equilibrium in which mental models of production accurately predict subsistence outcomes. This adaptation to new conditions may require a rapid learning rate and the ability to modify or abandon prior goals. Impulsivity and socially distributed information processing may have niche construction functions.

The number of adults in the household was associated with reduced time to recovery. This effect was independent of agricultural production and livestock ownership, suggesting other causal pathways. Parallel, distributed cognition is one possibility (Griere & Moffat 2003; Kronenfeld 2012; Theiner, Allen & Goldstone 2010; Tollefsen 2006). Multiple coresident adults
may think about and discuss adaptive problems as a group thus leading to improved “priors” for environmental prediction. Elaboration of group “parallel distributed processing” effects is beyond the scope of the present analysis, but further research concerning discussion networks and household decision making should examine predictive processing in small groups responding to shocks.

Sample size and the distribution of new subsistence regimes are likely important for replicating these results. The adaptive value of impulsivity for culture change and niche construction may depend on “bow-waves” or “leading edges” for new regimes. Niche construction benefits of impulsivity might be apparent only when new livelihoods are practiced by a relatively small proportion of households. Once a technological innovation has spread, then relative benefits of impulsivity may be reduced or costs increased, and one should simply choose an alternative among possible niches as they approach equal proportions. Models and simulations, similar to Kameda & Nakanishi (2002), McElreath (2016) and Perreault et al (2012), might reveal a point at which a new technology is sufficiently common to adopt the relevant cultural models rather than incurring costs of exploration. Such models may benefit from including “probabilistic cultural attraction” as a factor influencing cultural evolution (Claidière & Sperber 2007; Claidière, Scott-Phillips & Sperber 2014) where impulsivity is a mechanism altering attraction and promoting regime shifts in cultural cognition.

5. Conclusion

In general, progress in life history and cross-cultural personality psychology has been hampered by a lack of data from non-WEIRD (Henrich, Heine & Norenzyan 2010), small-scale and subsistence level populations where drug, alcohol, obesity, driving fast, etc. (the global development related externalities of impulsivity [see Lewis et al 2017]) are least common. This
lack of data from small-scale populations is particularly acute because health costs of impulsivity and FLH may be magnified in environments with large surpluses leading to over-nutrition, greater exposure to addictive substances, and potentially dangerous technology (e.g. automobiles and guns), thus obscuring the adaptive significance of mechanisms for life history strategies and niche construction.

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Data Availability
Data are available upon request to the author.

References Cited


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DOI:10.1016/j.euroecorev.2015.05.004


http://scholarcommons.usf.edu/jea/vol18/iss1/7


