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Bayesian Herders: Updating of Rainfall Beliefs in Response to External Forecasts

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Summary. — Temporal climate risk weighs heavily on many of the world's poor. Model-based climate forecasts could benefit such populations, provided recipients use forecast information to update climate expectations. We test whether pastoralists in southern Ethiopia and northern Kenya update their expectations in response to forecast information. The minority of herders who received these climate forecasts updated their expectations for below normal rainfall, but not for above normal rainfall. This revealed preoccupation with downside risk highlights the potential value of better climate forecasts in averting drought-related losses, but realizing any welfare gains requires that recipients strategically react to these updated expectations.

JEL classification — D84, O12, O13, Q16
Key words — information, risk, early warning systems, Africa, Kenya, Ethiopia

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1. INTRODUCTION

Information can be valuable when it facilitates improved decision making in the face of temporal uncertainty, such as that associated with rainfall fluctuations. Since climate variability can result in massive financial and human losses due to droughts, floods, and costly risk mitigation strategies, it may pay to have timely, reliable climate forecasts to help people choose optimal state-contingent livelihood strategies, both to avoid disaster and to capitalize on temporary, favorable states of nature. Recognizing the value seasonal climate forecasts could have to subsistence farmers and pastoralists [1] living in the arid and semi-arid lands (ASAL) of Sub-Saharan Africa (SSA) and elsewhere (e.g., Hudson, 2002), several development agencies have directed attention and funding to establishing Famine Early Warning Systems (FEWS) over the past two decades (Barrett, 2002; Walker, 1989). More recently, a big push has been made to augment FEWS with computer models of coupled atmospheric–oceanic circulation patterns that translate data on wind speed and direction, topography, and sea surface temperatures into seasonal precipitation forecasts issued one to six months ahead.

Simply producing and disseminating climate forecasts does not make them valuable to those who are the intended beneficiaries, however. If subsistence farmers and pastoralists living in the ASAL of SSA are to benefit directly from climate forecasting innovations, then several necessary conditions must be met.

(i) Computer-based climate forecasts must forecast local rainfall or rainfall-related outcomes, such as pasture quality or crop yields, reasonably accurately.

(ii) Local decision takers must receive external forecasts satisfying (i).

(iii) Those who receive these forecasts must update their prior climate beliefs in response to external forecasts.

(iv) Decision takers must then be able and willing to change behavior in response to updated climate beliefs.

Necessary condition (i) has been addressed adequately in the atmospheric sciences literature for several locations in Africa (Agatsiva, 1997; Barnston, Thiao, & Kumar, 1996; Beltrando & Camberlin, 1993; Cane, Eshel, & Buckland, 1994; Folland, Owen, Ward, & Colman, 1991; Hulme *et al.*, 1992a, 1992b; Ogallo, 1994). A companion paper that studies (ii) concludes that only a minority of East African pastoralists heard these forecasts and, perhaps surprisingly, that those who did receive the forecasts made little or no *ex ante* changes in their livelihood strategies after receiving climate forecasts (Luseno, McPeak, Barrett, Little, & Gebru, 2003). One possible explanation for the lack of *ex ante* behavioral changes in spite of receiving a climate forecast could be that pastoralists fail to update their climate expectations after receiving forecasts. The present paper seeks to establish whether or not there is evidence that herders update in response to climate forecasts, as proposed in condition (iii) above, in order to further advance understanding of why so little evidence of behavioral changes is found relating to question (iv). Using a unique data set collected among pastoralists and agropastoralists in southern Ethiopia and northern Kenya, an area that has suffered repeated serious droughts in recent years, we estimate whether those receiving climate forecast information change their beliefs about uncertain future states of nature and, if so, how.

To the best of our knowledge, this paper presents the first empirical study of beliefs updating either in a development context or in response to climate forecast information. We conclude that, despite their limited familiarity with computer-based forecasting methods and the existence of competing forecasts based on widely-accepted, indigenous methods, pastoralists who receive external climate forecasts indeed update their rainfall expectations, albeit asymmetrically. These herders update below normal rainfall beliefs readily in response to the computer-based forecast, but appear virtually to ignore the above normal forecast.

2. BELIEF UPDATING AND COGNITIVE BIASES

Uncertainty enters importantly into many economic decisions. When uncertain outcomes are assigned probabilities, uncertainty becomes risk and can, in theory, be more easily managed. Given probabilities on outcomes, and assuming economic agents behave rationally, economic theorists can devise models of expected utility and risk aversion to predict market outcomes. The objective probabilities required by such models, however, are mostly missing in reality. Instead, economic agents must formulate their own beliefs about uncertain outcomes and thus largely deal in subjective, not objective, probabilities. In formulating these subjective probabilities, people typically start with some initial (perhaps naïve) beliefs about underlying probability distributions, then commonly seek supplementary information. They then update their prior beliefs in response to new information, thereby generating a new, posterior subjective probability distribution.

Consider, for example, an individual i who initially believes an event will occur with probability π_i who receives from some external source a competing subjective probability, π_m, for the same event. Her updated conditional (posterior) subjective probability, $\pi_{i|m}$, can be expressed as [2]

$$\begin{aligned}\pi_{i|m} &= \delta_i\pi_i + (1-\delta_i)\pi_m \\ &= \pi_m + \delta_i(\pi_i - \pi_m),\end{aligned} \tag{1}$$

where $(1-\delta_i)$ is individual i's updating weight and indicates her confidence in π_m and its source.

Informational flows and the process of belief updating can directly affect behavior and market outcomes and has hence been the focus of considerable psychological and, increasingly, economic research. Hirshleifer and Riley (1992) propose a general framework based on traditional Bayesian updating rules and derive three useful propositions. First, an individual's confidence in his prior beliefs largely determines whether he seeks additional information and, if he seeks and receives it, how he processes it. This confidence is represented statistically in the tightness of the prior probability distribution. Second, the greater the individual's confidence in the message—represented by $(1-\delta_i)$ in (1)—the greater its effect on the individual's posterior probability distribution. Third, the more surprising a message relative to the individual's prior beliefs—represented by $(\pi_i - \pi_m)$ in (1)—the greater the updating effect. Regarding the second and third propositions, people typically update beliefs with a predictable bias toward the extremeness of a message (Griffin & Tversky, 1992; Tversky & Kahneman, 1974). Thus, a surprising message with little credibility may incite a greater updating effect than a credible one that differs only slightly from initial beliefs.

Testing these abstract propositions empirically is challenging because the updating of prior beliefs is fundamentally an unobservable cognitive process that is explicitly expressed only in rare circumstances. Consequently, empirical work on how people respond to new information relies either on data generated from clever experiments or on inference based on non-experimental data (see Rabin, 1998 for an excellent survey). One general aim of this research is to assess the effect of existing beliefs on the interpretation of new information. The anchoring-and-adjustment heuristic (Tversky & Kahneman, 1974) suggests that initial beliefs, or even irrelevant starting values if individuals are sufficiently inexperienced, tend to anchor one's processing of information. Adjustment away from this initial anchor in response to new information is typically insufficient (Bruner & Potter, 1964; Epley & Gilovich, 2001). Consequently, people who formulated their existing beliefs on weak evidence have difficulty interpreting subsequent information that contradicts these initial hypotheses, even if this new information is recognized to be more accurate (Bruner & Potter, 1964). [3]

In struggling to reconcile existing beliefs with new information, people often tend to ignore new information altogether, a tendency called belief perseverance, or proactively to misread the new evidence as supportive of existing hypotheses, a tendency called confirmation bias (Darley & Gross, 1983; Lord, Ross, & Lepper, 1979; Plous, 1991; Rabin & Schrag, 1999). These cognitive biases become especially pronounced when new information is genuinely ambiguous (Griffin & Tversky, 1992; Keren, 1987), but fail to disappear even when a person has expertise and training (Kahneman & Tversky, 1982; Tversky & Kahneman, 1982). Such biases can directly affect an individual's capacity to forecast an outcome after having processed new information, especially if the individual has a vested stake in the outcome in which case individual preferences introduce yet another cognitive bias (Kunda, 1990). As a consequence, preference-consistent information is taken at face value, while preference-inconsistent information is processed critically and subjectively (Ditto & Lopez, 1992; Hales, 2003).

Analysis of non-experimental data tends generally to corroborate the conclusions of the experimental literature reviewed above. Empirical analyses that study the cognitive processing of risk and subsequent forecasts of risky outcomes are especially relevant. Slovic (1987), in a classic study examining how people formulate risk judgments about chemical and nuclear technologies, concludes that while experts employ sophisticated risk assessment tools to evaluate hazards, most everyone else relies on intuitive risk judgments or risk perception. Noting experts' frustration with citizens' inability to formulate accurate perceptions of risk, Slovic (1987) points out that one should not expect disputes about risk to vanish when credible evidence is presented since strongly-held prior beliefs affect the way subsequent information is processed. Slovic observes that risk communication and management must consequently be structured as a two-way process in which both the public and the experts engage in a dialogue, an observation directly relevant to contemporary, largely top-down efforts to anticipate climate shocks in marginal areas of the developing world.

While experts in some contexts seem more Bayesian than non-experts (e.g., Roll, 1984), they are still subject to complex human emotions and cognitive limitations. In financial markets, for example, sunshine is significantly correlated with daily stock returns (Hirshleifer & Shumway, 2003). Even experts are not immune to feeling a bit more optimistic on sunny days—or on rainy days, if it is rain that is hoped for—and updating their expectations accordingly. Furthermore, experts' cognitive biases do not only arise from their general mood. Specialized financial analysts with training and experience often display systematic optimism, underreacting to negative information and overreacting to positive information (Easterwood & Nutt, 1999). Experience may be the best teacher, but new information is often read optimistically, rather than objectively, despite its tutelage. No one, it seems, is a perfect Bayesian. But how Bayesian are pastoralists in the Horn of Africa in response to computer-generated climate forecasts when they are likely to have limited, if any, personal experience with computer technology or forecasting models and when alternate, indigenous climate forecasting methods abound?

3. A MODEL OF CLIMATE FORECAST UPDATING

(a) *Climate beliefs, forecasts and updating*

In this section, we develop a simple model of an east African pastoralist's updating of climate beliefs and then derive two econometric approaches to test whether locals who receive external climate forecasts update their climate expectations. Assume there exist three possible precipitation states, above normal (A), normal (N) and below normal (B) rainfall, such that $s = \{A, B, N\}$ where the aridity of the locale implies that A is preferred to N, which is preferred to B. We use this formulation because seasonal climate forecasts issued in the Horn of Africa in fact follow this trinomial structure. The herder-farmer chooses among several feasible actions, including herd migration, livestock sales or slaughter, purchase of feed or veterinary inputs, crop or varietal choice, timing of planting, protection against pests, application of inorganic fertilizers, etc., which we denote as strategy vectors ($\underline{y} = \underline{1}, \ldots, \underline{Y}$). The outcomes ($C_{ys}$) of these strategies and states of nature can be described by a results matrix as follows: [4]

$$\begin{array}{cc|ccc|}
 & & \multicolumn{3}{c}{\text{States (s)}} \\
 & & A & N & B \\
 & 1 & C_{1A} & C_{1N} & C_{1B} \\
\text{Strategies } (\underline{y}) & \underline{2} & C_{2A} & C_{2N} & C_{2B} \\
 & \vdots & \vdots & \vdots & \vdots \\
 & Y & C_{YA} & C_{YN} & C_{YB}
\end{array}$$

The value of updating beliefs lies in the variability of outcomes conditional on the realized states of nature and the correlation between forecast probabilities and states of nature. If one strategy is optimal regardless of the state of nature or if the forecast is uncorrelated with observed states of nature, the decision taker generally gains nothing by updating beliefs. If forecasts are correlated with realized states and the optimal strategy is state contingent, however, it generally benefits decision makers to update probabilistic beliefs in response to informative signals received and adopt the strategy most beneficial for the anticipated state. The benefits associated with updating increase as the costs to switching strategies *ex post* increase and are highest *ceteris paribus* when switching strategies *ex post* is impossible. The value of updating one's beliefs can also increase as the set of strategies at one's disposal expands. For example, if wealthier households enjoy a broader range of productive options and the rank ordering of the returns to these strategies is state dependent, then the value of updating beliefs in response to a signal is an increasing function of wealth. Alternatively, those poorer subpopulations may have relatively few options available to them in terms of *ex ante* strategies so that there is limited value to updating as there is relatively little one can do with this information in terms of adopting a different strategy. As yet another possibility, individuals may simply have little motivation to update beliefs when they can switch strategies *ex post* in a low cost manner, which is arguably the case for migratory pastoralists of southern Ethiopia and northern Kenya. Thus the absence of behavioral responses to climate forecast receipt might reflect not the absence of updating but, instead, the fact that strategies can be adopted based on the realized state of nature rather than a forecast of the state of nature if production is sufficiently flexible *ex post*. We leave as a future topic for research whether the lack of significant changes in *ex ante* strategies reflects an inability to change strategies *ex ante* due to a lack of options or an ability to adapt *ex post* due to the flexibility of the production system. Our concern in this study is the narrower question of whether the limited *ex ante* response reported in our companion study does or does not reflect a failure to update beliefs in response to a forecast message. If forecast recipients do not update their prior beliefs, then extension of forecasts has negligible value. It is to the explicit question of the nature of updating in this setting that we now turn.

Let the unconditional prior beliefs distribution of individual i in village j be summarized by priors π_{ij}^{A}, π_{ij}^{N}, π_{ij}^{B} for states A, N, and B, respectively, with $\pi_{ij}^{A}+\pi_{ij}^{N}+\pi_{ij}^{B}=1$. In the present context, one's priors would be formed through past experience and, perhaps especially, by a rich array of indigenous climate forecasts universally available within pastoralist communities in the region. Within the region we study, every community has traditional methods such as interpreting stars, clouds, trees, wildlife behavior, the intestines of slaughtered livestock, dreams, or other phenomena used to issue predictions about the upcoming season's climate (Luseno *et al.*, 2003). In some cases, there are particular experts who are trusted in making these interpretations. In most communities, there is a great deal of conversation in the dry season before the rains fall discussing the various predictions that have been made in the area. Many of these methods generate long-lead, seasonal forecasts that roughly match the time scale of external, model-based forecasts. Virtually everyone within a community receives such indigenous climate forecasts (Luseno *et al.*, 2003), so we consider these forecasts to generate something along the lines of a common, location-specific component to each individual's prior due both to the high degree of discussion about these forecasts within the community and the presence of individuals who are viewed as particular experts in such forecasts in most of the communities studied. However, given the vast array of these methods, interpersonal variation in confidence in these methods (Luseno *et al.*, 2003), and the possibility that there may be multiple experts within a community, we also allow that within a community there can be some divergence of opinion. We will model this below as a village based consensus forecast that is modified by personal characteristics to arrive at individual specific subjective beliefs prior to receipt of external forecasts.

In the Horn of Africa, the Drought Monitoring Centre (DMC), based in Nairobi, is responsible for releasing climate forecasts, which are then disseminated through national meteorological agencies. A pastoralist who receives the DMC forecast has to decide how much to update his prior beliefs. If he fully believes the forecast, he may replace his prior with the DMC's published probabilities. If he has no confidence in the DMC forecasts, he may not update at all, remaining steadfast in his prior beliefs in the face of competing predictions. There are many reasons why pastoralists might have reservations about the validity or relevance of DMC forecasts: the broad DMC forecast is not conditioned on the specifics of his location; the forecast is solely with respect to rainfall volumes, not timing or rainfall-related outcomes; the forecasts originate from a black box operated by strangers; etc.

The updating equation that determines the pastoralist's posterior beliefs was presented as Eqn. (1), which (with updated notation) is given by

$$\pi_{ij|\mathrm{DMC}}^{s}=\pi_{\mathrm{DMC},j}^{s}+\delta_{ij}^{s}(\pi_{ij}^{s}-\pi_{\mathrm{DMC},j}^{s}), \tag{2}$$

where $\pi_{\mathrm{DMC},j}^{s}$ is the external forecast probability for state s. This updating equation simply states that an individual's posterior probability is computed as her prior probability adjusted for the difference between the DMC's forecast and her own prior probability multiplied by δ^{s}_{ij}, an updating weight representing the individual's willingness to abandon her own prior in favor of the DMC forecast probability. [5] Where modern and traditional climate forecasters differ, the seemingly simple updating weight represents a complex cognitive process that involves the "objective" information value of these competing forecasts, but also surely entails more subjective assessments of their source and means of delivery. Note, importantly, that this updating weight, δ^{s}_{ij}, is potentially state-specific implying that individuals may process above normal rainfall forecasts differently than below normal rainfall forecasts.

Subtracting $\pi^{s}_{\mathrm{DMC},j}$ from both sides of Eqn. (2), this updating equation becomes

$$d^{s}_{ij|\mathrm{DMC}} = \delta^{s}_{ij} d^{s}_{ij}, \tag{3}$$

where $d^{s}_{ij} = (\pi^{s}_{ij} - \pi^{s}_{\mathrm{DMC},j})$ is the "prior gap," the difference between the prior and the DMC forecast, and $d^{s}_{ij|\mathrm{DMC}} = (\pi^{s}_{ij|\mathrm{DMC}} - \pi^{s}_{\mathrm{DMC},j})$ is the "posterior gap," the difference between the posterior and the DMC forecast. In this formulation, $\delta^{s}_{ij} = 0$ implies complete updating (i.e., the prior gap closes completely), $\delta^{s}_{ij} = 1$ implies no updating (i.e., the prior and posterior gap are identical), and $0 < \delta^{s}_{ij} < 1$ implies partial updating. While receipt of the DMC forecast is an obvious precondition to updating, non-recipients will still play an important role in estimating δ^{s}_{ij} as described in the next subsection.

The simplified updating equation in (3) assumes that the magnitude of d^{s}_{ij} is the only piece of new information relevant to the updating process. In principle, the *sign* of d^{s}_{ij}—whether the forecast is "good" or "bad" news relative to the prior—may also influence the updating of climate beliefs, especially in the presence of cognitive biases toward optimism or pessimism. The updating equation in (3) explicitly allows for updating asymmetries *between* states, but disallows this sort of updating asymmetry *within* state. As a matter of survival, both kinds of updating asymmetry seem defensible: surely herders should treat bad news about below normal rainfall more seriously than good news about above normal rainfall. Such asymmetric updating, although less motivated by physical survival, has been found in other contexts, as discussed above. To test for updating asymmetry due to good *versus* bad news *within* state, we modify the updating equation slightly as

$$|d^{s}_{ij|\mathrm{DMC}}| = \delta^{s,+}_{ij} |d^{s,+}_{ij}| + \delta^{s,-}_{ij} |d^{s,-}_{ij}|, \tag{4}$$

where for $s = \{A, B\}$

$$d^{A,+}_{ij} = \begin{cases} d^{A}_{ij} & \text{if } \pi^{A}_{\mathrm{DMC},j} > \pi^{A}_{ij}, \\ 0 & \text{otherwise}, \end{cases} \quad d^{A,-}_{ij} = \begin{cases} 0 & \text{if } \pi^{A}_{\mathrm{DMC},j} > \pi^{A}_{ij}, \\ d^{A}_{ij} & \text{otherwise}, \end{cases}$$
$$d^{B,+}_{ij} = \begin{cases} d^{B}_{ij} & \text{if } \pi^{B}_{\mathrm{DMC},j} < \pi^{B}_{ij}, \\ 0 & \text{otherwise}, \end{cases} \quad d^{B,-}_{ij} = \begin{cases} 0 & \text{if } \pi^{B}_{\mathrm{DMC},j} < \pi^{B}_{ij}, \\ d^{B}_{ij} & \text{otherwise}. \end{cases} \tag{4a}$$

These modified prior gaps reflect whether the DMC forecast is received as bad or good news. The forecast is bad news if it assigns a higher likelihood to below normal rainfall or lower likelihood to above normal rainfall relative to the individual's prior. By splitting the prior gap into positive and negative gaps and transforming both the prior and posterior gaps into absolute values, this specification allows for updating asymmetry *within* state. For example, $1 = \delta^{A,-}_{ij} < \delta^{A,+}_{ij} \leqslant 0$ would suggest that herders dismiss bad news about the probability of above normal rainfall, but update in response to good news.

(b) *Econometric approaches*

The updating model discussed above lends itself to reduced-form and structural econometric estimation. The reduced-form approach simply tests whether—controlling for individual traits and village effects—recipients' rainfall beliefs are different than non-recipients' beliefs. In this approach, observed beliefs are modeled as

$$\pi^{s}_{ij|\mathrm{DMC}} = f^{s}(\mathbf{x}_i, \mathbf{v}, R_{ij}) + \varepsilon^{s}_{ij}, \tag{5}$$

where $\mathbf{x}_i$ is a vector of individual variables, $\mathbf{v}$ is a vector of village dummies, $R_{ij} = 1$ for DMC recipients and 0 otherwise, and ε^{s}_{ij} is a stochastic error term. [6] The estimated coefficient on R_{ij} in (5) captures systematic differences in rainfall beliefs between recipients and non-recipients—a necessary but not sufficient condition for updating. Note that the individual and village variables in (5) implicitly control for recipients' unobserved prior rainfall beliefs. In order to test for updating more rigorously, we must recover these priors explicitly and directly estimate the updating weights in (3) and (4).

Our data provide only a single belief observation for each individual, expressed as a trinomial probability forecast, which was collected after the DMC issued its March–May 2001 forecast. For those who did not receive the DMC forecast, this set of beliefs represents both their prior and posterior beliefs. For recipients, on the other hand, this observed set of beliefs represents their posterior beliefs, which are different from their priors if any updating has occurred. Thus, a primary challenge to estimating econometrically the model in (3) is that π_{ij}^{s}—a critical baseline from which any updating is measured—is unobservable for recipients, precisely the individuals whose updating behavior we wish to estimate.

Prior beliefs π_{ij}^{s} are founded on complex cognitive processes that are difficult either to model explicitly or to elicit directly. Nonetheless, observable traits provide signals about how an individual processes information and formulates beliefs. Those with formal education, perhaps especially scientific training, may learn about natural phenomena such as climate differently from those without formal education and may therefore come to very different conclusions. Beliefs are also shaped by prevailing social norms, so where an individual lives clearly matters. In particular, local knowledge about microclimatic variation and indigenous forecasts matter to an individual's rainfall expectations. Individual i's prior, π_{ij}^{s}, can thus be written explicitly as

$$\pi_{ij}^{s} = g^{s}(\mathbf{x}_i, \mathbf{v}) + \varepsilon_{ij}^{s}. \tag{6}$$

Since π_{ij}^{s} is observed for non-recipients and is latent otherwise, π_{ij}^{s} can be modeled as a selection model where the outcome equation is shown in (6) and the selection equation specifies the factors that affect receipt of the DMC forecast. [7] Household characteristics such as ownership of a radio and education, and village characteristics such as proximity to major roads importantly affect receipt of DMC forecasts. Correcting the outcome equation in (6) for this selection bias yields parameter estimates that can be used to estimate priors for recipients of the DMC forecast. With these estimated priors in hand, we can then focus exclusively on forecast recipients to estimate the mean updating weights in Eqns. (3) and (4).

4. DATA AND ESTIMATION RESULTS

(a) *Data*

The data used in this paper were collected as part of the broader Pastoral Risk Management (PARIMA) project of the USAID Global Livestock Collaborative Research Support Program. Approximately 30 households in each of 10 villages were surveyed, four in southern Ethiopia (Dida Hara (DH), Dillo (DI), Finchawa (FI), Wachile (WA)) and six in northern Kenya (Dirib Gumbo (DG), Kargi (KA), Logologo (LL), Ngambo (NG), North Horr (NH), and Suguta Marmar (SM)). Climate-focused surveys were conducted in March 2001 immediately prior to the long rains season, which typically begin late in March and continue through May. A few of our Kenyan sites (KA, NH) had experienced rare, early (*furmat*) rains in January and February 2001 that seem to have induced unusual optimism in these two sites about the upcoming rains, as manifest in unconditional subjective probability distributions that weighted above normal or normal rainfall much more heavily than other sites.

During the pre-rains survey, enumerators asked household heads whether they had heard forecasts of the upcoming season's rainfall patterns, the source(s) of such forecasts heard, their confidence in the forecast information, past use of forecast information, etc. A previous round of surveys among these households had gathered information on ownership of radios, educational attainment and other household-specific characteristics that may matter to an individual's priors, her updating of climate beliefs or both. Together, the information from these different modules allows us to establish who received computer-based DMC climate forecast.

The survey also included a novel elicitation of respondents' subjective probability distribution over the upcoming climate state. Household heads were given 12 stones and asked to distribute them into three piles, each pile representing a different state (again, $s = \{A, N, B\}$), with the number of stones in each pile representing the individual's prediction about the likelihood that precipitation in the coming long rains season would be above normal ($s = A$), normal ($s = N$) or below normal ($s = B$). While we have encountered some development professionals who believe that pastoral populations with little formal education relate mostly to deterministic forecasts and may not be able to conceptualize probabilistic forecasts, only 16 of 244 households offered degenerate forecasts in which all 12 stones were placed in a single pile. Interestingly, all of these degenerate forecasts suggested extreme optimism (i.e., $(A, N, B) = (100\%, 0\%, 0\%)$), and 11 of these 16 were from North Horr, a village that experienced the unusual *furmat* rains before the survey was conducted, as noted above. For our entire sample (including both recipients and non-recipients of forecasts) the average prediction for the coming rainy season was $\pi^A = 42\%$, $\pi^N = 37\%$, $\pi^B = 21\%$ for northern Kenya, and $\pi^A{=}27\%$, $\pi^N = 48\%$, $\pi^B = 25\%$ for southern Ethiopia. Before the climate survey was fielded, the DMC issued its own trinomial probabilistic forecast for this rainy season for both northern Kenya ($\pi^A_{DMC,j} = 25\%$, $\pi^N_{DMC,j} = 40\%$, $\pi^B_{DMC,j} = 35\%$ for all villages j in Kenya) and southern Ethiopia ($\pi^A_{DMC,j} = 35\%$, $\pi^N_{DMC,j} = 40\%$, $\pi^B_{DMC,j} = 25\%$ for all villages j in Ethiopia). [8] This would suggest that the DMC forecast for northern Kenya was more pessimistic than the average respondent in this area's forecast, and that the DMC forecast for southern Ethiopia was more optimistic than the average respondent in this area's forecast. A map of the DMC forecasts is shown in Figure 1.

The DMC forecasts imply that the coming rainy season was not expected to be an "extreme climate" season as would be the case under El Nino conditions of 1997–98 or the droughts of 1999–2000 or 2005–06. In the sense that at least a 25% chance or better is given to any of the three states occurring in the respective areas, these forecasts appear somewhat vague. [9] Furthermore, these forecasts cover broad regions and project over the entire long rains season. These temporal and spatial averages are therefore not intended to capture microvariability of rainfall patterns. That the DMC forecasts for the long rains of 2001 did not communicate any appreciable likelihood of extreme conditions and were necessarily temporal and spatial generalizations would seem to suggest that the "extremeness" of the information was low, making a measurable updating effect unlikely (Griffin & Tversky,

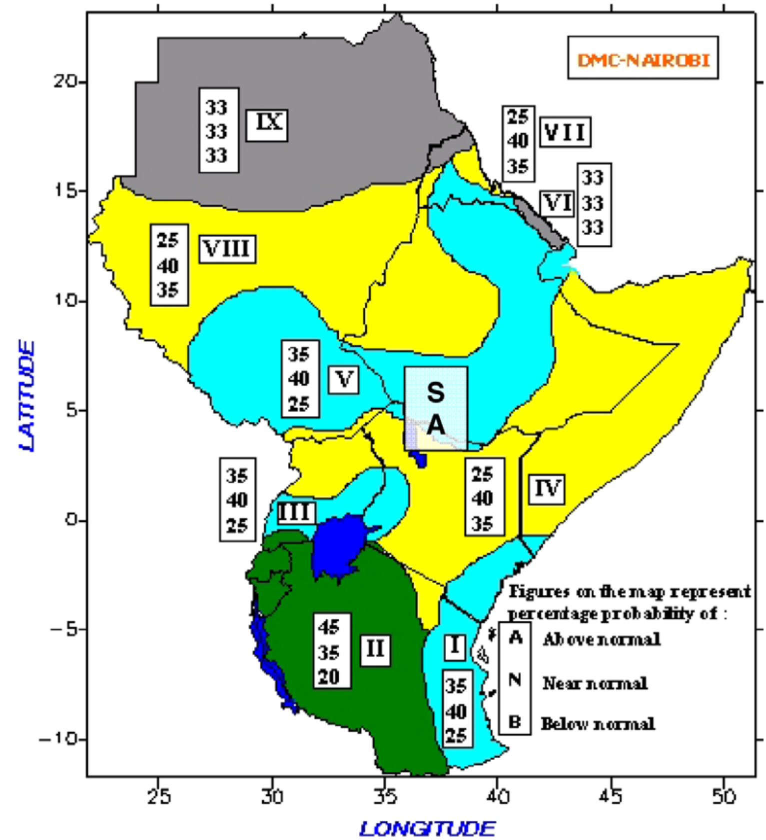

Figure 1. *March–May 2001 seasonal rainfall forecast from the Drought Monitoring Centre with study area (SA) indicated.*

Table 1. *Descriptive statistics*

Variable ($N = 245$)	Mean	Std. dev.	Min. (%)	Max. (%)
Male {0, 1}			0 (30%)	1 (70%)
Age	47.9	14.3	22	98
Education	0.75	2.3	0 (87%)	13 (<1%)
TLU	12.5	22.2	0 (18%)	200
Cultivation {0, 1}			0 (56%)	1 (44%)
Seasonal rainfall expectations (%)				
Above normal	34.9	26.8	0 (2%)	100 (6%)
Normal	40.6	23.5	0 (9%)	83.3 (7%)
Below normal	22.3	20.3	0 (20%)	83.3 (<1%)

1992; Tversky & Kahneman, 1974). On the other hand, the ambiguity of the forecast likely amplifies any cognitive biases (e.g., optimism or pessimism) that might exist in the processing of this information (Griffin & Tversky, 1992; Keren, 1987).

After cleaning the data and matching baseline households to households represented in the climate survey, we have data on 245 households. Table 1 provides descriptive statistics of some key variables in this data set. Only 37 households in our sample received the DMC forecast. That so few received the forecast seems to be partly due to the forecasts being broadcast in Swahili and Amharic, the national languages of Kenya and Ethiopia, respectively, that are not understood by many pastoralists without formal education since their vernaculars have different linguistic roots. This feature of the DMC forecast implies that this section's analysis tests the updating effect conditional upon external forecasts broadcast in national languages being heard and understood by the recipient.

(b) *Estimation approaches and results*

We begin with a simple approach where we specify the reduced-form updating Eqn. (5) as

$$\pi^{s}_{ij} = \beta_0 + \beta_1 MALE_{ij} + \beta_2 EDU_{ij} + \beta_3 \ln TLU_{ij} + \beta_4 CULT_{ij} + \beta_5 RADIO_{ij} + \beta_6 R_{ij} + \boldsymbol{\phi}'\mathbf{v} + \varepsilon^{s}_{ij}. \quad (5')$$

The vector of village dummies represents, among other things common to households in a single location, the variety of traditional forecasting methods used in an area and a great deal of pre-rainy period discussion about the various predictions and interpretations that can lead community members to converge on a community consensus forecast. Individuals will still differ in how they evaluate and interpret these various methods based on their personal characteristics, thus generating variation within the community in individuals' subjective forecasts. In addition to village dummies, we therefore include a variety of personal characteristics: $MALE = \{0, 1\}$, EDU is years of formal education, $\ln TLU$ is the natural logarithm of household herd size in tropical livestock units, [10] $CULT = \{0, 1\}$ is a dummy variable indicating whether the household cultivates seasonal crops, [11] and $RADIO = \{0, 1\}$ indicates whether the household owns a radio. Gender, education, and age may affect an individual's climate beliefs *inter alia* by shaping one's understanding and processing of information and independence of thought. Possession of a radio enables an individual to access an array of external information (other than the DMC forecast) that may influence the formulation of climate beliefs. Since households that cultivate cannot respond to inaccurate *ex ante* climate expectations as flexibly as a purely pastoralist household can—because crops cannot move while livestock can—whether a household cultivates crops and the size of its herd may be important determinants of rainfall beliefs. Herd size is also a strong correlate of wealth, which likely affects rainfall beliefs. Wealthy households are better able to cope with climate shocks and, so, may care relatively less about accurate rainfall predictions. Conversely, wealth may be correlated with latent characteristics that affect cognitive processing of information. For example, wealthy households might be wealthy precisely because they are relatively good at assessing and strategically responding to information. Wealthy households might also have access to broader networks of information. After controlling for these village fixed effects and these individual effects, we test whether recipients and non-recipients evince different rainfall beliefs, a necessary condition for updating, with the hypothesis test H_0: $\beta_6 = 0$ *versus* H_1: $\beta_6 \neq 0$.

We address two econometric issues before estimating the reduced-form equation in (5′). First, the dependent variable in (5′) has distinctly discrete properties. Individual predictions about states A, N, and B were solicited using 12 stones and the resulting probabilities are therefore measured in increments of $1/12 = 8.33\%$. We allow for (White) heteroskedastic errors to account for the effect this discreteness has on the variance of the errors. [12] Second, π_{ij}^{s} is potentially censored at 0 and 100. While only 2% of our observed above normal beliefs are censored, 19% of below normal beliefs are censored at zero. Despite various drawbacks to Tobit estimation in the present context, [13] we therefore estimate (5′) using both Tobit techniques and OLS for below normal beliefs.

We report reduced-form estimation results in Table 2. As we find little difference between the Tobit and the OLS results, we confine our attention to the OLS results for simplicity. The village dummies have a strong and significant influence on rainfall beliefs. For above (below) normal rainfall expectations, a joint significance test on these village fixed effects yields an F value of 18.55 (26.06) with a p-value of zero. Something approaching a community consensus appears to prevail with respect to climate expectations in our survey sites. While individual variables have some effect, the only individual variable that consistently and significantly influences these expectations is whether the individual received a forecast or not. Compared to non-recipients, those who received the DMC forecast estimate a higher probability of above average rainfall and lower probability of below average rainfall. [14] Although we cannot infer from this that recipients update their beliefs, a measurable difference between recipients and non-recipients is an obvious necessary condition for updating.

For a clearer test of updating, we estimate the updating equation in (3), which requires

Table 2. *Reduced-form estimation of rainfall beliefs*

Dep. var: π_{ij}^{s} % Censored (lower; upper):	Above normal (<1%; 7%)		Below normal (19%; 0)			
Variable	Coef.	Std. err.[a]	Coef.	Std. err.[a]	Tobit Coef.	Tobit Std. err.[b]
Intercept	39.6^{**}	(5.5)	16.2^{**}	(2.8)	14.6^{**}	(5.0)
Male {0, 1}	4.3	(2.9)	−2.0	(2.1)	−2.4	(2.6)
Education (years)	−0.55	(0.48)	−0.26	(0.36)	−0.20	(0.48)
ln *TLU*	−0.21	(1.1)	−0.16	(0.84)	0.12	(1.14)
Cultivation {0, 1}	−3.9	(3.5)	−3.0	(2.0)	−3.4	(3.7)
Radio {0, 1}	6.8^{*}	(3.6)	0.94	(2.4)	0.9	(3.0)
R_{ij} {0, 1}	12.2^{**}	(4.5)	-7.3^{**}	(2.3)	-9.1^{**}	(3.6)
Village dummies[c]						
Dirib Gumbo	-12.7^{**}	(5.4)	10.2^{**}	(3.7)	10.7^{**}	(5.2)
Dida Hara	-26.5^{**}	(4.6)	41.9^{**}	(2.8)	43.0^{**}	(5.8)
Dillo	-16.1^{**}	(6.0)	25.3^{**}	(4.5)	27.0^{**}	(4.6)
Finchawa	-23.5^{**}	(5.4)	-6.1^{**}	(2.4)	−6.2	(7.7)
Kargi	−7.7	(7.2)	15.9^{**}	(4.9)	17.1^{**}	(5.6)
Logologo	-34.3^{**}	(4.8)	11.8^{**}	(3.1)	14.4^{**}	(5.9)
Ngambo	8.5	(6.6)	3.8	(3.0)	3.7	(6.4)
North Horr	18.1^{**}	(8.5)	−2.0	(3.7)	−6.9	(5.5)
Suguta Marmar	19.3^{**}	(6.6)	0.4	(3.7)	−3.4	(4.7)
Adj-R^2	0.45		0.54			
N	245		245		245	

* and ** indicate statistical significance at the 10% and 5% levels.
[a] OLS standard errors are White heteroskedastic standard errors.
[b] Tobit standard errors are structurally heteroskedastic as a function of age, education, livestock, and average village precipitation.
[c] Wachile omitted.

estimated priors for recipients in addition to their observed posteriors. To recover these priors, we use a selection model to control for the possibility that receipt of the DMC forecast might be non-random. This allows us to control for the possibility that what we might otherwise interpret as changes that reflect response to receipt of the forecast might instead capture something about the forecast made by the types of people who are more likely to seek out forecasts. This requires two distinct estimation steps. First, we estimate the probability of an individual not receiving the forecast. Second, we use this estimated probability as a control variable in estimating the subjective beliefs of those not receiving the forecast. This provides unbiased estimates of the parameters that shape the rainfall beliefs of non-recipients. We then use these estimated parameters to estimate priors for DMC forecast recipients.

We start by estimating the likelihood that a respondent did not receive the forecast. We specify this selection equation as

$$\begin{aligned}(1 - R_{ij}) = {} & \gamma_0 + \gamma_1 MALE_{ij} + \gamma_2 EDU_{ij} + \gamma_3 AGE_{ij} \\ & + \gamma_4 AGE^2_{ij} + \gamma_5 \ln TLU_{ij} + \gamma_6 CULT_{ij} \\ & + \gamma_7 RADIO_{ij} + \gamma_8 KENYA_j \\ & + \gamma_9 ROAD_j + \varepsilon^{\mathrm{p}}_{ij}, \end{aligned} \tag{7}$$

where $KENYA = \{0, 1\}$ distinguishes villages in Kenya from those in Ethiopia and $ROAD = \{0, 1\}$ indicates whether the village is within 10 km of a major road. Following Heckman's technique this selection equation is estimated as a Probit model. We specify the outcome equation in (5) as

$$\begin{aligned}\pi^{\mathrm{s}}_{ij} = {} & \beta_0 + \beta_1 MALE_{ij} + \beta_2 EDU_{ij} + \beta_3 \ln TLU_{ij} \\ & + \beta_4 CULT_{ij} + \beta_7 RADIO_{ij} + \boldsymbol{\phi}'\mathbf{v} + \beta_\lambda \lambda + \varepsilon^{\mathrm{f}}_{ij}, \end{aligned} \tag{8}$$

where $\mathbf{v}$ is a vector of village dummies and λ is the selection correction term. Note that we use AGE, AGE^2, $KENYA$, and $ROAD$ to identify the selection effect associated with forecast receipt. Estimation results of this selection model are shown in Table 3. The selection equation results suggest that younger, more educated individuals who have radios and reside in villages close to main roads are more likely to hear a forecast, as seems intuitive. As a somewhat puzzling result, those involved in cultivation appear less likely to hear a forecast. This may be related to wealth since cultivation in much of our area is adopted by the poor who have lost their herds (correlation between $CULT$ and TLU is -0.28). This important connection between cultivation and receipt of climate forecasts merits further attention.

As in Table 2, the outcome equation results show that rainfall beliefs are strongly influenced by village effects. In contrast to the reduced-form results, there is some evidence that individual characteristics influence subjective rainfall beliefs after taking into account the selection issue. Males who have smaller herds and a radio but do not cultivate appear to have the most optimistic beliefs about the likelihood of above normal rainfall. Lastly, note that the coefficient on λ, the selection correction term, is insignificant, suggesting that receipt of the DMC forecast may not be endogenous.

However, to be methodologically cautious, we report estimates of prior rainfall beliefs that have been corrected for possible selection bias. We use the coefficient estimates in Table 3 and observed characteristics of respondents to estimate forecast recipients' priors, which then allows us to estimate the updating equation and test directly for updating among recipients. Since the updating equation in (3) is univariate, we can graphically depict the updating weight as the slope on a graph of recipients' estimated priors against their observed posteriors, measured as differences from the DMC forecast. In this graph, shown in Figure 2, the 45° line represents no updating and the horizontal axis represents complete updating. A point in the northeast quadrant implies that both the estimated prior and the observed posterior beliefs place greater probability on the event than did the DMC forecast, while a point in the southwest quadrant implies lower probability was placed on the event by the individual than the DMC. A point in the northwest quadrant implies a prior less than the DMC forecast, but a posterior greater than the DMC forecast. Conversely, a point in the southeast implies a prior greater than the DMC forecast but a posterior below the DMC forecast. Points between the horizontal line and the 45° line suggest updating in response to the DMC forecast.

The difference between recipients' estimated updating of above normal rainfall beliefs (A) and their below normal rainfall beliefs (B) is striking. Recipients as a group seem to update below normal beliefs far more readily than above normal beliefs. Seventy-eight percent of recipients are in the updating region for below

Table 3. *Selection model results*

Dependent variable	Selection equation $(1-R)$		Outcome equation π^A		Outcome equation π^B	
	Coef.	Std. err.	Coef.	Std. err.	Coef.	Std. err.
Intercept	0.0003	(1.11)	37.2**	(7.0)	11.76**	(5.25)
Male {0, 1}	0.015	(0.26)	5.3*	(3.1)	−2.39	(2.37)
Education (years)	−0.10**	(0.047)	−1.0	(1.4)	−1.06	(1.03)
Age	0.081*	(0.045)				
Age^2 (÷100)	−0.072*	(0.041)				
ln *TLU*	−0.133	(0.097)	−0.96*	(1.3)	0.09	(1.02)
Cultivation {0, 1}	0.62**	(0.25)	−4.2*	(4.7)	−1.04	(3.5.8)
Radio {0, 1}	−0.48*	(0.27)	11.5**	(5.0)	−2.50	(3.77)
Kenya {0, 1}	−0.39	(0.27)				
Road {0, 1}	−0.81**	(0.29)				
Village dummies[b]						
Dirib Gumbo			−11.8	(6.2)	25.70**	(4.57)
Dida Hara			−9.5**	(6.6)	12.87**	(4.96)
Dillo			−22.6**	(6.8)	46.03**	(5.14)
Finchawa			−18.8	(6.4)	−4.30	(4.64)
Kargi			−6.5	(7.3)	21.79**	(5.48)
Logologo			−24.8**	(7.2)	10.06*	(5.21)
Ngambo			13.9**	(6.6)	5.75	(4.86)
North Horr			17.9**	(7.2)	2.09	(5.40)
Suguta Marmar			23.9**	(6.6)	0.69	(4.84)
Lambda			−3.3	(18.1)	10.18	(13.48)
R^2	0.18[a]		0.42		0.53	
N	245		208		208	

* and ** indicate statistical significance at the 10% and 5% levels.
[a] Estrella (1998) pseudo-R^2.
[b] Wachile omitted.

normal rainfall, but only 6% are in this region for above normal rainfall. This unmistakable pattern suggests that recipients take the DMC forecast for below normal rainfall more seriously than their above normal forecast. Note also that recipients' estimated priors were systematically more optimistic than the DMC forecasts. Seventy-three percent of the prior gaps for above normal rainfall were positive and all of the prior gaps for below normal rainfall were negative, indicating that recipients placed much higher probability on above average rainfall and much lower probability on below average rainfall than did the official DMC forecast.

To gain more insight into the pattern in the data illustrated in Figure 2, we estimate the mean updating weight for beliefs about these two states with the specification implied by Eqn. (3)

$$d^s_{ij|\mathrm{DMC}} = \delta d^s_{ij} + \varepsilon^s_{ij}, \qquad (3')$$

where ε^s_{ij} is a heteroskedastic error term. As suggested by the updating model, there is no intercept term in this specification. Corresponding to the slope of the 45° line in Figure 2, the no updating hypothesis test is H_0: $\delta = 1$ *versus* H_1: $\delta < 1$. The corresponding full updating hypothesis test is H_0: $\delta = 0$ *versus* H_1: $\delta > 0$.

There are again some econometric issues to address before estimating Eqn. (3′). Once again, our dependent variable in (3′) has discrete properties, albeit less pronounced than in the reduced-form approach. There are only two relevant DMC forecasts given the geographic coverage of the survey data, one for northern Kenya ($\pi^A_{\mathrm{DMC,K}} = 25\%$, $\pi^B_{\mathrm{DMC,K}} = 35\%$) and another for southern Ethiopia ($\pi^A_{\mathrm{DMC,E}} = 35\%$, $\pi^B_{\mathrm{DMC,E}} = 25\%$). With these two different forecasts for each rainfall state, there are now 24 possible values for d^s_{ij}. We again allow for heteroskedastic errors to account for this discreteness. Next, d^s_{ij} is potentially doubly censored: lower censored at $(-\pi^s_{\mathrm{DMC},j})$ and upper censored at $(1-\pi^s_{\mathrm{DMC},j})$. We estimate (3′) using both Tobit techniques and OLS for completeness. Lastly, the presence

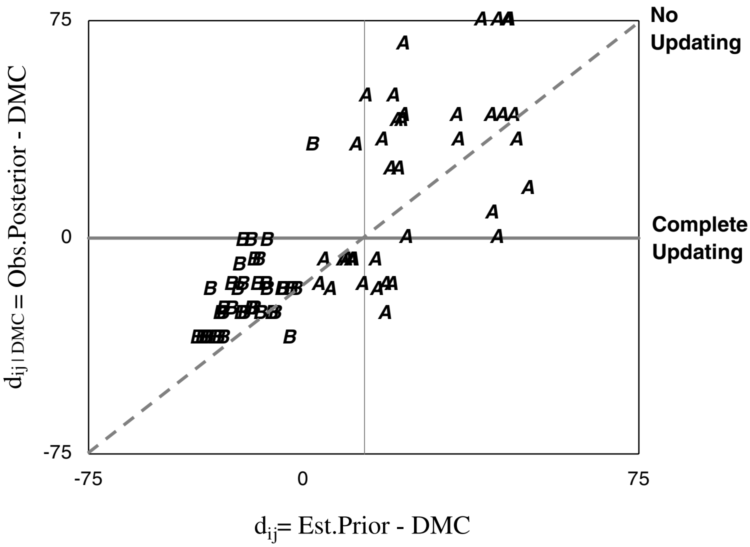

Figure 2. *Recipients' estimated prior and observed posterior climate beliefs for above normal (A) and below normal (B) seasonal rainfall.*

of estimated priors from the selection model in (3′) implies that standard errors in any estimated updating equation are biased and inconsistent due to a standard generated regressors problem. We bootstrap the standard errors to remedy this problem.

Results from the estimation of (3′) are shown in the top panel of Table 4. Consistent with Figure 2, we find evidence of updating of below, but not above, normal rainfall beliefs. For above normal rainfall beliefs, we fail to reject the no updating null H_0: $\delta^A = 1$ and, hence, easily reject the full updating null H_0: $\delta^A = 0$. For below normal rainfall beliefs, however, we reject the no updating null H_0: $\delta^B = 1$ in both the OLS and Tobit models, but reject—narrowly in the Tobit model—the full updating null H_0: $\delta^B = 0$. These results thus provide a strong evidence of partial updating in response to below normal rainfall forecasts but no

Table 4. *Updating equation results*

Dep. var: $d^{s}_{ij\|_{DMC}}$ % Censored (lower; upper)	Above normal rainfall (3%; 14%)			Below normal rainfall (35%; 3%)		
	OLS	Tobit		OLS	Tobit	
		Coef.	Marginal		Coef.	Marginal
d^{s}_{ij}	1.23^{**}	1.39^{**}	1.20	$0.66^{\circ,**}$	$0.42^{\circ\circ,**}$	0.55
(Std. err.)[a]	(0.30)	(0.22)		(0.19)	(0.21)	
Adj-R^2	0.34			0.27		
Dep. var: $\|d^{A}_{ij\|DMC}\|$						
$\|d^{A,+}_{ij}\|$	1.33^{**}					
	(0.25)					
$\|d^{A,-}_{ij}\|$	1.32^{**}					
	(0.22)					
N	37	37		37	37	

$^{\circ}$ and $^{\circ\circ}$ indicate rejection of H_0: $\delta = 1$ over H_1; $\delta < 1$ at significance levels 10% and 5%.
[a] Standard errors are bootstrapp and White heteroskedastic.
** Statistical significance (H_0: $\delta = 0$) at the 10% and 5% levels.

updating in response to above normal rainfall forecasts, thus suggesting that updating is asymmetric *between* rainfall states.

To test for updating asymmetries *within* states—that is, whether recipients incorporate good news about a given state differently than bad news—we now turn to the estimation of Eqn. (4) that captures such asymmetries in updating. Relative to estimated priors, the DMC above normal forecast was bad news for 27% of recipients, but the DMC below normal forecast was bad news for 100% of recipients. Consequently, we can only test for asymmetries *within* states for the above normal state. We estimate Eqn. (4) for s = A as

$$|d^{\mathrm{A}}_{ij|\mathrm{DMC}}| = \delta^{\mathrm{A},+}|d^{\mathrm{A},+}_{ij}| + \delta^{\mathrm{A},-}|d^{\mathrm{A},-}_{ij}| + \varepsilon^{\mathrm{A}}_{ij}, \qquad (4')$$

where the positive and negative prior gaps, $d^{\mathrm{A},+}_{ij}$ and $d^{\mathrm{A},-}_{ij}$, are defined in (4a). The relevant hypothesis test for asymmetric updating *within* the above normal rainfall state is H_0: $\delta^{\mathrm{A},+} = \delta^{\mathrm{A},-}$ *versus* H_1: $\delta^{\mathrm{A},+} \neq \delta^{\mathrm{A},-}$. Based on the results in the lower panel of Table 4, we clearly fail to reject this null and find no evidence of asymmetric updating *within* the above normal state. This result is preliminary at best since the estimated prior gaps of the 10 recipients who received the DMC above normal forecast as good news are not too far from zero (see Figure 2). Furthermore, this result of course suggests nothing about possible asymmetries *within* the below normal state, for which we had only bad news observations. Further research is therefore needed before any conclusions can be made about whether pastoralists update asymmetrically *within* state.

5. CONCLUSION

In a world of considerable temporal uncertainty, economic performance—indeed, mere survival in environments as harsh as the rangelands of the Horn of Africa—often depends considerably on the magnitude and speed with which decision takers update prior beliefs in response to relevant new information. In agrarian societies, one of the most profound sources of uncertainty concerns what type of rainy season lies ahead. As efforts accelerate to disseminate computer-generated climate forecasts in the Horn of Africa and other regions of the developing world subject to frequent, severe climate shocks, questions of how such forecasts might contribute to improved well being and better risk management grow rapidly in importance.

Optimism about climate forecasting's potential as a development tool implicitly depends, however, on previously untested assumptions that intended beneficiaries receive external forecasts, that they update prior beliefs in response to this information, and that they will adopt a strategy in response to this updated belief that reduces risk exposure and improves well being. Yet in cultures that have long used indigenous forecasting methods, where access to modern media and familiarity with computer-based technologies are limited, and where external forecasts are generated at a relatively coarse spatial scale, it is an open question whether regional forecasts based on sophisticated computer models and disseminated by outsiders will readily gain the acceptance necessary to induce behavioral changes at the household level leading to the desired ends of reducing vulnerability and alleviating poverty.

This paper presents the first direct study of the issue of belief updating in this context, exploring how the subjective rainfall expectations of pastoralists in southern Ethiopia and northern Kenya change in response to receipt of computer-generated climate forecasts. Before discussing our findings on updating, we again stress that the subsample of those who heard an external forecast with which to update beliefs was a very small portion of the overall sample. Poor access to modern media (e.g., radio, television, newspapers) and the languages used in modern climate forecasts limit the access of most herders to external climate forecasts in east Africa. Indeed, only 15% of our respondents heard the forecast generated by the DMC, indicating that existing delivery systems are not very effective at making these forecasts widely available. Clearly, there is a need to rethink information dissemination strategies if the objective is to make these forecasts broadly accessible to potential users.

Our more nuanced research question considers how those who are in the small group of forecast recipients process climate forecast information. Simply put, the motivation for investigating this question is that there is not much point to rethinking the dissemination strategy in an effort to reach the other 85% of the pastoralist population if current recipients effectively ignore this information. Based on the observed and inferred behavior of recipients, we conclude that recipients as a group do update their below normal rainfall beliefs, but not their above normal rainfall beliefs. We estimate this updating asymmetry *between* states by formulating recipients' posterior rainfall beliefs as a weighted average of their own prior belief and the DMC forecast. For below normal rainfall, the average weight on the DMC forecast is roughly 1/3, but for above normal rainfall, it is statistically zero. Climate forecasters can take some comfort in this evidence of updating in response to probabilistic seasonal rainfall forecasts. This suggests that herders who hear the DMC forecast change their expectations in response to drought predictions—even if on average they appear to ignore the prediction of above normal rainfall.

We cannot tell whether pastoralists' failure to adopt external climate forecasts fully reflects skepticism about the external forecast, limited use due to the coarse scale of the forecast, greater confidence in local level traditional forecast methods, or some other reason(s); we leave this as a topic for future research. In addition, while it also seems plausible that herders might also update asymmetrically *within* state—that is, respond differently to good *versus* bad news about a given state—we find no preliminary evidence of such *within* state asymmetries for above normal forecasts, but are unable to test for these asymmetries with below normal forecasts due to data limitations.

If forecast recipients indeed update their expectations in response to below normal DMC forecasts, do they then manage their herds and households differently in response to these updated expectations? In a companion study, we found little evidence that receipt of forecast information leads to significant behavioral changes (Luseno *et al*., 2003). The results of the current study suggest this is not due to any inability of pastoralists to process forecast information. This allows us to identify a critical question for further research. Why, if people get a forecast, believe it is reliable, and update their predictions as described in the current study, do we have so little evidence of resulting behavioral changes? If we had found that people were not updating, that would have suggested a need for extension efforts to help people comprehend and process this information. But since they seem able to comprehend and process external forecasts information already, what is limiting the critical final step that takes updated beliefs into adoption of state-contingent strategy that reduces vulnerability?

These findings provide one new, and important, piece of information that will help sort out this puzzle. That is, people update below normal rainfall predictions but do not update above normal rainfall predictions. Why might that be? One interpretation is that more can be done in anticipation of below normal rainfall, thus making updating more valuable in this domain. The suite of options for drought coping are wide, varied, and enacted with some frequency in this region (Morton, 2006; Ndikumana *et al*., 2000; Oba, 2001; Pratt, 2002), especially as compared to the options for the relatively rare cases when above average rainfall turns from a blessing into a curse (Little, Mahmoud, & Coppock, 2001). Given that we observed major herd losses in this area in 1997–98 during the El Nino rains, the devastating losses during the drought of 1999–2000, and are currently receiving reports of equivalent losses due to poor rains, there is reason to believe that the suite of strategies available are at best only partially effective in reducing vulnerability. This would suggest that development efforts to help pastoralists cope better with climate uncertainty should focus not only on better means of delivering information about expected climate patterns and improving these predictions, but perhaps especially on supporting interventions that expand the set of strategies that can be adopted upon receipt of such information. Such interventions have been the focus of a growing body of research in recent years in this area (Aklilu & Wekesa, 2001; Morton, 2006; Morton & Barton, 2002). If both access to information and access to strategies that can be adopted in response to this information are expanded, improved information delivery might be able to help reduce poverty and vulnerability. Taken in isolation, however, efforts that only focus on improving information delivery have limited impact.

NOTES

1. Pastoralists are nomadic or transhumant herders whose livelihoods depend primarily on extensive grazing of livestock in arid and semi-arid regions. Agropastoralists couple extensive grazing with crop cultivation.

2. In its more general form, Bayesian updating rules involve the ratio of a joint probability that two events occur and the unconditional probability that one of the events occur. The updating rule presented here is a

special case of this general rule in which a prior is updated with a competing subjective probability. For purposes of this paper, including the empirical analysis herein, this simple updating rule suffices.

3. An extreme case is modeled in the abstract by Rabin and Schrag (1999) who show that an agent may come to believe with near certainty in a false hypothesis despite receiving an infinite amount of information.

4. Although this matrix does not directly relate to the empirical implementation that follows, because we look solely at the updating process and not at outcomes, it is nonetheless important to situate the updating process within a broader analytical framework of choice under uncertainty.

5. In the literature on Bayesian updating, confidence in competing probabilities is often represented as a variance that the individual assigns to the source. The appropriate updating weight in such a case is one that is some monotonically increasing function of inverse variance (i.e., the lower the variance assigned to a source, the more confidence and the larger the updating weight).

6. Note that the s superscript on f accounts for the possibility that above and below normal precipitation expectations are formulated in slightly different manners. We will exploit this difference in the estimation.

7. In this case, a selection bias model is justified because receipt of the DMC forecast is non-random and because unobserved elements of the error term in Eqn. (6) also influence who receives the forecast (e.g., family ties to extension agents, friends with radios, etc.).

8. The DMC did not issue country specific forecasts. As it happens, the dividing line between DMC forecast regions IV and V lay in northern Kenya, to the north of our Kenyan sites and to the south of our Ethiopian sites.

9. East African annual rainfall patterns are bi-modal. This forecast is for the "long rains," which occur earlier in the year than the "short rains." By construction, the naïve uniform trinomial forecast is (33, 33, 33), that is, not radically different from what DMC broadcast for the long rains. As pointed out by a reviewer, the fact that the announced forecast is not all that different from the naïve forecast could be due to the fact that forecasts for the long rains have less predictability than the short rains, given current knowledge.

10. One *TLU* equals 0.7 camels, 1 cattle, or 10 goats or sheep. This is a standard aggregation method.

11. The cultivation dummy variable is based on the dichotomous observation of whether the household ever cultivated crops over the year prior or year following the 2001 long rains we study. The results are invariant to including only cultivation prior to the long rains of 2001, thereby obviating the potential endogeneity of cultivation after the start of the 2001 long rains to respondents' climate beliefs.

12. The variance at observable values is likely inflated relative to neighboring, unobserved values (e.g., 7%). The typical remedy for discrete properties like this is correcting standard errors for the inherent heteroskedasticity. We are indebted to J.S. Butler for calling this issue to our attention.

13. Tobit estimation requires an assumption about the distribution of the residuals.

14. This may seem inconsistent with the earlier observation that the sample prior placed greater (lesser) weight, on average, on above (below) normal rainfall in the coming season. This merely reflects the difference between conditional and unconditional differences, however, and the fact that the results of Table 2 reflect variation within sites only, given control for site dummies, while the overall average effect encompasses differences among villages as well.

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