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

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Abstract

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 and find that they indeed do, albeit with a systematic bias towards optimism. In their systematic optimism, these pastoralists are remarkably like Wall Street's financial analysts and stockbrokers. If climate forecasts have limited value to these pastoralists, it is due to the flexibility of their livelihood rather than an inability to process forecast information.

Keywords: information, expectations, risk, uncertainty, weather, early warning systems

JEL Classification Numbers: D84, O12, O13, Q16

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I. 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[4] living in the arid and semi-arid lands (ASAL) of Sub-Saharan Africa (SSA) and elsewhere, 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 having climate forecasts does not make them valuable, however. If the poor 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 and believe external forecasts satisfying (i).

(iii) Those who receive and believe 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, et al. 1996, Beltrando and Camberlin 1993, Cane, et al. 1994, Folland, et al. 1991, Hulme, et al. 1992a, Hulme, et al. 1992b, Ogallo 1994). A companion paper that studies (ii) and explores the complex issues surrounding (iv) concludes that East African pastoralists make no *ex ante* changes in their livelihood strategies after receiving climate forecasts

[4] 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.

(Luseno, et al. 2003). Pastoralists' non-responsiveness to climate forecasts may be explained by the inherent flexibility of pastoralism, relative to agriculture for example, but may also be due to pastoralists failing to update their climate expectations after receiving forecasts. Since the implications of these potential explanations are quite different, one must first clearly establish why pastoralists appear to disregard climate forecasts in practice before expecting to leverage, if possible, climate forecasts on their behalf. The present paper seeks to establish which of these competing explanations is valid by addressing question (iii). 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 and believing 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 in ways that suggest a cognitive bias towards optimism. In the systematic optimism they display when interpreting information, east African pastoralists appear remarkably similar to financial analysts on Wall Street (see Easterwood and Nutt 1999).

The plan for the remainder of the paper is as follows. In Section II, we briefly review the extant literature on updating. Section III outlines a model of updating that structures our econometric analysis in Section IV. We present conclusions in Section V.

II. Belief Updating & 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[5]

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

where δ_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 δ_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 $(\pi_m - \pi_i)$ in (1)—the greater the updating effect. Of the second and third, people typically update beliefs with a predictable bias towards the extremeness of a message (Griffin and Tversky 1992, Tversky and 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 and 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

[5] 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.

initial anchor in response to new information is typically insufficient (Bruner and Potter 1964, Epley and 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 and Potter 1964).[6]

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 and Gross 1983, Lord, et al. 1979, Plous 1991, Rabin and Schrag 1999). These cognitive biases become especially pronounced when new information is genuinely ambiguous (Griffin and Tversky 1992, Keren 1987), but fail to disappear even when a person has expertise and training (Kahneman and Tversky 1982, Tversky and 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 and 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.

One's familiarity and experience with risk directly affects one's capacity to make accurate judgments about risk and forecasts. For example, only a fraction of homeowners who had voluntarily tested the radon levels in their homes and learned that these levels were high enough to merit mitigation actually followed through with the recommended mitigation (McClelland, et al. 1991).

[6] An extreme case is modeled in the abstract by Rabin and Schrag (1999) who show that an agent may come to believe

Radon, however, presents an invisible and unfamiliar risk to most homeowners. That few homeowners apparently updated their perceptions about radon risks even after being informed that radon levels were high is therefore understandable. Experts, on the other hand, are better able to process information and to update beliefs when appropriate. Investigating the futures market for concentrated orange juice, a commodity that is highly sensitive to frost, Roll (1984) finds a significant relationship between returns on orange juice futures and errors in National Weather Service temperature forecasts for the central Florida region where most juice oranges are grown. Most participants in commodity markets seem to update their beliefs predictably in response to temperature forecasts, and, consequently, prices on orange juice futures incorporate these expectations. Only when these incorporated forecasts are wrong do traders respond by adjusting prices.[7]

While experts seem more Bayesian than non-experts, they are still subject to complex human emotions and cognitive limitations. In financial markets, sunshine is significantly correlated with daily stock returns (Hirshleifer and 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 and 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 some of the world's least educated and technology savvy subpopulations, such as pastoralists in the Horn of Africa?

III. A Model of Climate Forecast Updating

A. Updating Herders' Beliefs

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, N, B} where the aridity

with near certainty in a false hypothesis despite receiving an infinite amount of information.

[7] There is, however, an important difference between forecasting market outcomes and forecasting climate outcomes. Because market outcomes are endogenous, forecasting them is essentially an exercise in forecasting others' forecasts. Incidentally, this introduces the possibility that additional information might make an agent worse off if it leads her to overpredict how much information others have (the so-called 'curse of knowledge' (Camerer, et al. 1989)). In contrast, climate outcomes are purely exogenous to others' forecasts of them and are therefore not subject to this 'curse'.

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, crop or varietal choice, timing of planting, protection against pests, application of inorganic fertilizers, etc. For simplicity, we refer to a vector of actions as strategies ($\underline{y}=\underline{1},\ldots,\underline{Y}$). The outcomes ($C_{ys}$) of these strategies and states of nature can be described by a results matrix as follows:[8]

$$
\begin{array}{cc|ccc|}
\multicolumn{5}{c}{\text{States (s)}} \\
 & & A & N & B \\
\text{Strategies } (\underline{y}) & 1 & C_{1A} & C_{1N} & C_{1B} \\
 & \underline{2} & C_{2A} & C_{2N} & C_{2B} \\
 & \vdots & \vdots & \vdots & \vdots \\
 & Y & C_{YA} & C_{YN} & C_{YB}
\end{array}
$$

The value of updating beliefs lies in the variability of outcomes conditional on 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. 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 also increases 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. Subpopulations with relatively few options available to them, but with some capacity to switch strategies *ex post*–like the pastoralists of southern Ethiopia and northern Kenya who we study–might therefore benefit little from updating their beliefs. Finding updating in our subject population is thus relatively strong evidence in favor of the hypothesis that even non-experts with a limited stake indeed update beliefs in Bayesian fashion.

[8] 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

Let the unconditional prior beliefs distribution of individual i in village j be summarized by prior means π_{ij}^{A}, π_{ij}^{N}, π_{ij}^{B} for 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 at least one traditional forecaster[9] who interprets stars, clouds, trees, wildlife behavior, the intestines of slaughtered livestock, dreams or other phenomena and issues predictions about the upcoming season's climate.[10] 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 treat these as a common, location-specific component to each individual's prior.

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. If a pastoralist receives the DMC forecast and has complete confidence in the validity and relevance of this external forecast, he is likely to update completely and immediately, replacing his priors with the DMC's set of probabilities, which he implicitly considers to be objective. A pastoralist who has reservations about the validity or relevance of the DMC forecast –because the broad DMC forecast is not conditioned on the specifics of his location for example – treats it as a set of competing subjective probabilities and must reconcile his own prior beliefs with the DMC forecast. The updating equation that determines his posterior beliefs was presented as equation (1), which (with updated notation) is given by

(2) $$\pi^{s}_{ij|DMC} = \pi^{s}_{ij} + (\pi^{s}_{DMC,j} - \pi^{s}_{ij})\delta_{ij}$$

where $\pi^{s}_{DMC,j}$ is the mean of the external forecast probability distribution for state s and s={A, N, B}. 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_{ij}, an updating weight representing the individual's willingness to abandon her own prior in favor of the DMC forecast probability.[11] Where modern and traditional climate forecasters differ,

analytical framework of choice under uncertainty.

[9] These traditional forecasters are called *laibon* in Samburu, *yub* or *raga* in Boran/Gabra, and by other names among the remaining ethnic groups in our sample.

[10] In addition to forecasting seasonal rainfall, these traditional seers also predict other events (e.g., raids on livestock) and are often contracted to mix potions or cast spells.

[11] 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.)

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.

If the DMC forecast was perfectly, uniformly disseminated and receiving the forecast was costless, then the simple updating model above would suffice for empirical investigation. However, access to external climate forecast information is unevenly distributed in the region. Some people actively seek out the forecast, primarily via radio but also, to a far lesser degree, from neighbors, extension agents and printed media. Others may inadvertently hear the forecast, for example, over the radio at a local tea shop when they visit town. Moreover, even those receiving the DMC forecast may express no confidence in the forecast. We must adapt the updating equations above to reflect these facts. If an individual does not receive the DMC forecast, the updating weight on $\pi^{s}_{DMC,\,j}$ should be zero. Likewise if an individual who receives the DMC forecast does not believe it, this weight should be negligible. A more appropriate updating equation is therefore

(3) $$\pi^{s}_{ij|DMC} = \pi^{s}_{ij}[1 - RC_{ij}\delta_{ij}] + \pi^{s}_{DMC,j}[RC_{ij}\delta_{ij}]$$

where RC_{ij}=1 if individual i in village j receives and has confidence in the DMC forecast and RC_{ij}=0 otherwise. When δ_{ij}=1 and RC_{ij}=1, individual i is willing to adopt completely the DMC's forecast as her own (i.e., treats the DMC's forecast as an objective probability). By subtracting $\pi^{s}_{DMC,j}$ from both sides, the updating equation in (3) can be further simplified to

(4) $$d^{S}_{ij|DMC} = d^{S}_{ij} - d^{S}_{ij}RC_{ij}\delta_{ij}$$

where $d_{ij}^{s}=(\pi_{ij}^{s}-\pi^{s}_{DMC,j})$ and $d^{s}_{ij|DMC}=(\pi^{s}_{ij|DMC}-\pi^{s}_{DMC,j})$. Note that when RC_{ij}=0, $d_{ij}^{s}= d^{s}_{ij|DMC}$ since information not received could not have affected the individual's climate beliefs. When RC_{ij}=1, however, $|d_{ij}^{s}|>|d^{s}_{ij|DMC}|$ implies that the person has updated his beliefs towards the DMC forecast and that $0>\delta_{ij}>1$. When RC_{ij}=1, complete updating (δ_{ij}=1) is implied by $d_{ij}^{s}\neq 0$ and $d^{s}_{ij|DMC}=0$.

B. Econometric Approaches to Estimating Updating

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 forecast. For those who either did not receive or did not believe the DMC forecast (i.e., RC_{ij}=0), this set of beliefs represents both their prior and posterior beliefs. For those with RC_{ij}=1, 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 above is that π_{ij}^{s}—a critical baseline from which any updating is measured—is unobservable for individuals with RC_{ij}=1, precisely the individuals whose updating behavior we wish to estimate. There are two econometric approaches worth considering when addressing this challenge. Both approaches rely on $d^s_{ij|DMC}$ as a dependent variable, but differ in how they treat unobservable priors for those with $RC_{ij}=1$.

<u>Direct Approach:</u> The direct approach involves directly recovering π_{ij}^s for individuals who receive and believe the DMC forecast. This requires an explicit model of π_{ij}^s, but enables one to estimate (4) directly. Because the equation in (4) has no intercept, this specification estimates two regression lines constrained to go through the origin – one for the control group ($RC_{ij}=0$) and one for the treatment group ($RC_{ij}=1$). While the slope of the control regression line is one by construction, the slope of the treatment regression line is unconstrained and estimated as the coefficient δ_{ij}. This coefficient thus represents the conditional mean updating weight implied by the treatment group.

Prior beliefs (π_{ij}^s) are founded on complex cognitive processes that are difficult either to model explicitly or to elicit for direct empirical investigation. Nonetheless, external traits provide signals about how an individual processes information and formulates beliefs. In particular, those with formal education, especially scientific training, may learn differently from those without formal education and may therefore come to very different conclusions than the uneducated. As with most individual beliefs, climate beliefs are also partly a function of prevailing social norms. Community level covariates – such as available indigenous forecasts – thus matter to an individual's priors. Individual i's prior, π_{ij}^s, can thus be written as a function of a vector of individual characteristics, $\underline{x}_{ij}$, a vector of village characteristics, $\underline{z}_j$ and an error term to account for the many unobservable factors (e.g., mood) that affect an individual's cognitive processing of information, as follows:[12]

(5) $$\pi_{ij}^s = f^s(\underline{x}_{ij}, \underline{z}_j, \varepsilon_{ij}^f)$$

Since π_{ij}^s is observed if $RC_{ij}=0$ and is latent otherwise, π_{ij}^s can be modeled as a selection model where the outcome equation is shown in (5) and the selection equation specifies the factors that affect whether an individual receives and believes the DMC forecast.[13] Household characteristics such as ownership of a radio and education, and village characteristics such as nearness to major roads

[12] 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.

[13] In this case, a selection bias model is justified because receipt and confidence in the DMC forecast is non-random and because unobserved elements of the error term in equation (5) also influence who receives the forecast (e.g., family ties to extension agents, friends with radios, etc.).

importantly determine whether an individual receives and believes the DMC forecasts. Thus, the selection equation is given by

$$RC_{ij} = p(\underline{x}_{ij}, \underline{z}_j, \varepsilon^p_{ij}) \tag{6}$$

Correcting the outcome equation in (5) for this selection bias yields parameter estimates that can be used to estimate $\hat{\pi}^s_{ij}$ for those receiving and believing the DMC forecast, thereby recovering their prior beliefs. With these priors in hand, the updating equation in (5) and the mean updating weight can be estimated directly.

Indirect Approach: Whereas the direct approach recovers unobservable priors directly, the indirect approach involves an implicit formulation of π_{ij}^s. This reduced-form approach does not permit direct estimation of the updating equation in (4), but allows for a broader investigation into the factors that affect the belief updating process. Since the updating weight in (4) cannot be estimated directly in this approach, δ_{ij} must also be defined implicitly. There are several factors that presumably affect δ_{ij}. Specifically, individual and village characteristics influence an individual's disposition to assimilate the DMC's forecasts by updating her priors, suggesting that the updating weight can be written as the following function

$$\delta_{ij} = h(\underline{x}_{ij}, \underline{z}_j, RC_{ij}, \varepsilon^h_{ij}) \tag{7}$$

After controlling for individual and village characteristics, which affect both the formulation of π_{ij}^s as shown in (5) and δ_{ij} as shown in (7), the indirect approach seeks to ascertain whether $d_{ij|DMC}^s$ is smaller for an individual m who received and believed the external forecast (RC_{mj}=1) than for an individual n who did not (RC_{nj}=0). More formally,

$$\begin{aligned} d^s_{ij|DMC} &= g^s(\pi^s_{ij}, \delta_{ij}, RC_{ij}, \upsilon_{ij}) \\ &= g^s(f^s(\underline{x}_{ij}, \underline{z}_j, \varepsilon^f_{ij}), h(\underline{x}_{ij}, \underline{z}_j, RC_{ij}, \varepsilon^h_{ij}), RC_{ij}, \upsilon_{ij}) \\ &= g^s(\underline{x}_{ij}, \underline{z}_j, RC_{ij}, \upsilon^*_{ij}) \end{aligned} \tag{8}$$

As presented thus far, $d_{ij|DMC}^s$ can be positive or negative, depending on whether the DMC forecast is more or less favorable than individual i's observed forecast. This raises the question: might pastoralists systematically react differently to bad news than to good, just like the financial analysts of Wall Street (see Easterwood and Nutt 1999)? In addressing this question, we will refer to the DMC forecast as 'pessimistic' if it assigns greater likelihood to below normal seasonal rainfall than recipients had previously believed ($\pi_{ij}^B<\pi_{DMC,j}^B$) or that above normal seasonal rainfall is less likely ($\pi_{ij}^A>\pi_{DMC,j}^A$).

We hypothesize that, once received, the DMC forecast should have two important dimensions relevant to the updating process: magnitude (i.e., distance from prior) and sign (i.e., whether it is 'good' or 'bad').

To account explicitly for potential asymmetries in updating, equation (8) can be modified as

$$\left| d^{s}_{ij|DMC} \right| = h^{s}(\underline{x}_{ij}, \underline{z}_{j}, RC_{ij}, (\overline{d^{s}_{-DMC,j}} \times RC_{ij}), \varepsilon_{ij}), \tag{9}$$

where

$$\begin{aligned} \overline{d^{B}_{-DMC,j}} &= \left(\frac{1}{n_{-DMC,j}} \sum_{i=1}^{n_{-DMC,j}} \left(\pi^{B}_{ij} \middle| RC_{ij} = 0 \right) \right) - \pi^{B}_{DMC,j} \\ \overline{d^{A}_{-DMC,j}} &= \pi^{A}_{DMC,j} - \left(\frac{1}{n_{-DMC,j}} \sum_{i=1}^{n_{-DMC,j}} \left(\pi^{A}_{ij} \middle| RC_{ij} = 0 \right) \right) \end{aligned} \tag{9a}$$

where $n_{-DMC,j}$ is the number of individuals in village j who did not receive and believe the DMC forecast, and $\overline{d^{s}_{-DMC,j}}$ is the difference between the traditional forecast-based climate consensus in village j (i.e., uninfluenced by the DMC forecast) and the DMC forecast for village j. As defined in (9a), $\overline{d^{s}_{-DMC,j}} > 0$ implies that the DMC forecast represents 'good news' to those who receive it and this interpretation holds whether s=A or s=B.[14] The interaction term $(\overline{d^{s}_{DMC,j}} \times RC_{ij})$ therefore picks up whether those receiving the DMC forecast consider it 'good' or 'bad' news, as well as how 'good' or 'bad' this forecast is relative to the traditional forecast-based village consensus. This interaction term effectively proxies for the interaction term in (4), with the added advantage of allowing the effect of the DMC forecast on the updating process to be decomposed into a sign effect and a magnitude effect.

IV. 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 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 information and who expressed confidence in that information.[15]

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). Despite the common belief that relatively uneducated populations such as these relate mostly to deterministic forecasts and are not able to conceptualize probabilistic forecasts, only 16 of 244 households offered degenerative forecasts in which all 12 stones were placed in a single pile. Interestingly, all of these degenerative 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. Before the climate survey was fielded, the DMC issued its own trinomial probabilistic forecast for this rainy season for both northern Kenya ($\pi_{DMC,j}^{A}$=25%, $\pi_{DMC,j}^{N}$=40%, $\pi_{DMC,j}^{B}$=35% for all villages j in Kenya) and southern Ethiopia ($\pi_{DMC,j}^{A}$=35%, $\pi_{DMC,j}^{N}$=40%, $\pi_{DMC,j}^{B}$=25% for all villages j in Ethiopia).[16] A map of these forecasts is shown in Figure 1.

[14] Given a multimodal trinomial forecast (i.e., $\pi_{DMC}^{A}>\pi_{DMC}^{N}$ and $\pi_{DMC}^{B}>\pi_{DMC}^{N}$), this formulation would indicate that the external forecast is simultaneously received as 'good' and 'bad'. As with most climate forecasts, the external forecast and 'climate consensus' used in this paper is unimodal so this hypothetical problem is irrelevant.

[15] The post-rains survey asked the same households if they believe the forecasts to have been accurate. *Ex post* expressions of accuracy were very strongly correlated with *ex ante* expressions of confidence. The *ex ante* confidence measure thus seems to capture the strength of respondent's belief in the new forecast information.

[16] 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.

Because 2001 was not expected to be an 'extreme climate' year as would be the case under El Nino conditions, these forecasts appear somewhat vague.[17] 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 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 and Tversky 1992, Tversky and Kahneman 1974). On the other hand, the ambiguity of the forecast likely amplifies cognitive biases in the processing of this information (Griffin and Tversky 1992, Keren 1987).

After cleaning the data and matching baseline households to households represented in the climate survey, we have data on 244 households, of which 37 received and 30 both received and expressed some confidence in 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 being broadcast in national languages.

B. Econometric Approaches & Issues

Direct Approach: To implement the direct approach, we proceed in two steps. First, we recover the priors, π_{ij}^{s}, of those who receive and believe the DMC forecast using a selection model following Heckman's method. Second, we use these estimated priors along with the observed priors of the remaining respondents to estimate directly the differenced updating equation in (4).

In the outcome equation of the selection model (equation (5)), the vector of individual characteristics, $\underline{x}_{ij}$, includes truly individual variables such as gender (MALE=1 if male, 0 if female), education (EDU=years of formal education) and age (AGE in years, as well as AGE^2), plus household characteristics such as whether the household cultivates seasonal crops (CULT=1 if cultivates, 0 otherwise),[18] how many tropical livestock units (TLU)[19] are owned by the household and whether the

[17] By construction, the naïve trinomial forecast is (33, 33, 33), i.e., not radically different from what DMC broadcast.

[18] 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.

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

household owns a radio (RADIO=1 if owns radio, 0 otherwise). The vector of village characteristics, $\underline{z}_j$, includes a dummy variable for Kargi and North Horr, which experienced the atypical *furmat* rains that seem to have induced unusual optimism about the coming rainy season (FURMAT=1 if in KA or NH, 0 otherwise) and whether it is within ten kilometers from a main road (ROAD=1 if near road, 0 otherwise). The resulting specification for the outcome equation is

$$\begin{aligned}\pi_{ij}^{s} &= \beta_0 + \beta_1 MALE_{ij} + \beta_2 EDU_{ij} + \beta_3 AGE_{ij} + \beta_4 AGE_{ij}^2 \\ &+ \beta_5 CULT_{ij} + \beta_6 TLU_{ij} + \beta_7 RADIO_{ij} + \beta_8 FURMAT_j + \beta_9 ROAD_j + \varepsilon^{f}{}_{ij}\end{aligned} \tag{10}$$

The selection equation involves the same explanatory variables as the outcome equation in (10), but replaces FURMAT with a Kenyan dummy variable (KENYA=1 if the village is in Kenya, 0 if in Ethiopia) as follows:

$$\begin{aligned}RC_{ij} &= \gamma_0 + \gamma_1 MALE_{ij} + \gamma_2 EDU_{ij} + \gamma_3 AGE_{ij} + \gamma_4 AGE_{ij}^2 \\ &+ \gamma_5 CULT_{ij} + \gamma_6 TLU_{ij} + \gamma_7 RADIO_{ij} + \gamma_8 KENYA_j + \gamma_9 ROAD_j + \varepsilon^{p}{}_{ij}\end{aligned} \tag{11}$$

where the receipt and confidence variable (RC_{ij}) is calculated as a dummy variable that equals 1 if the individual received and expresses at least some confidence in the DMC forecast and 0 otherwise.[20] Following Heckman's technique this selection equation is estimated as a Probit model.

Once corrected for possible selection bias, the estimated coefficients of the outcome equation in (10) can be used to estimate $\hat{\pi}_{ij}^{s}$ for those whose priors are unobservable (RC_{ij}=1). The updating equation in (4) can then be directly estimated as

$$d_{ij|DMC}^{s} = \delta_1 d_{ij}^{s} + \delta_2 d_{ij}^{s} RC_{ij} + \varepsilon_{ij}^{s} \tag{12}$$

where $d_{ij}^{s} = d_{ij|DMC}^{s} = (\pi_{ij}^{s} - \pi_{DMC,j}^{s})$ if RC_{ij}=0, and $d_{ij}^{s} = (\hat{\pi}_{ij}^{s} - \pi_{DMC,j}^{s})$ and $d_{ij|DMC}^{s} = (\pi_{ij|DMC}^{s} - \pi_{DMC,j}^{s})$ if RC_{ij}=1. The coefficient δ_2 is an estimate of the mean updating weight for the households surveyed that received and believe the DMC forecast. Referring to the updating equation in (4), the null hypotheses of interest here are

$H1_o$: $\delta_1=1$	$H1_A$: $\delta_1 \neq 1$
$H2_o$: $\delta_2=0$	$H2_A$: $\delta_2<0$
$H3_o$: $\delta_2=-1$	$H3_A$: $\delta_2 \neq -1$

The H1 null merely reflects the identity between prior and posterior beliefs in the absence of any updating. H2 and H3 are our focus, with rejection of the H2 null indicating that updating indeed

[20] Those who received the DMC forecast were asked whether they had no confidence, some confidence or high confidence in these forecasts. In creating the RC_{ij} dummy variable, all forecast recipients who expressed some or high confidence were assigned RC_{ij}=1. Recipients expressing no confidence in the forecast were assigned RC_{ij}=0.

occurs and failure to reject the H3 null indicating consistency with a model of complete, immediate updating, wherein the external forecast is accepted as an objective probability.

There are three econometric issues to address before estimating the selection bias model and updating equation of the direct approach. [21] First, the dependent variables in the updating equation in (12) have distinctly discrete properties. There are only two relevant DMC forecasts given the geographic coverage of the survey data, one for northern Kenya ($\pi_{DMC,K}{}^{A}$=25%, $\pi_{DMC,K}{}^{B}$=35%) and another for southern Ethiopia ($\pi_{DMC,E}{}^{A}$=35%, $\pi_{DMC,E}{}^{B}$=25%). Furthermore, 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%. Since there are two different DMC forecasts for each state, there are 24 possible values for $d_{ij}{}^{s}$ for s={A, B}. Because the observed frequency is zero for several possible values, $d_{ij}{}^{s}$ actually takes on less than 24 values in our data. Estimation will thus allow for heteroscedasticity to account for the discrete nature of the dependent variables and for the effect this discreteness has on the variance of the errors.[22]

Secondly, $d_{ij}{}^{s}$ is potentially doubly-censored. Theoretically, $d_{ij}{}^{s}$ is lower-censored at ($-\pi_{DMC,j}{}^{s}$) and upper-censored at ($1-\pi_{DMC,j}{}^{s}$). Estimation of the updating equation in (12) could account for this censored data using Tobit estimation, but this would require an assumption about the distribution of the residuals. An additional problem with applying Tobit techniques in the present context is that heteroscedasticity can only be introduced structurally (i.e., one must specify a conditional variance equation). Due to the complex form of the heteroscedasticity introduced by the discreteness of the dependent variables, a less restricted correction for heteroscedasticity (e.g., White 1980) is preferable. Whether the benefits outweigh these limitations of Tobit estimation depends on the degree of

[21] The possible endogeneity of RC_{ij} is another possible issue. Based on our discussions with respondents, we doubt this is a serious problem with our data. Specifically, there is little evidence that the pastoralists included in our survey actively sought the DMC forecast, which would be the obvious source of endogeneity bias. We nonetheless experimented with a proxy for RC_{ij} to address the problem, but the proxy was so poor that it introduced measurement error problems that were more serious than the potential endogeneity problem it aimed to remedy. Although uninformative, these results are available from the authors by request.

Also note that it is reasonable to assume that an individual's propensity to update given that she receives the DMC forecast is state-dependent. It is reasonable, however, to expect that the random error terms in the s=B and s=A equations are correlated. This type of link between equations normally justifies the use of Seemingly Unrelated Regression (SUR) techniques in order to improve estimation efficiency. We believe the efficiency gains over OLS estimation are modest since the independent variables are nearly identical. Although efficiency gains could be greater in the nonlinear censored regression model, we believe this potential gain is still limited and choose not to use simultaneous Tobit methods.

[22] This discreteness is analogous to employment data collected by surveys in which most respondents' predictably claim to work 15, 20, 30, or 40 hours per week. In such cases, the variance at these values is likely inflated relative to neighboring integers (e.g., 39). The typical remedy for discrete properties like this is correcting standard errors for the inherent heteroscedasticity. We are indebted to J.S. Butler for this analogy.

censoring. The degree of censoring on d_{ij}^s,[23] while modest, persuades us to estimate the updating equation in (12) using both OLS and Tobit techniques.

Lastly, because our estimation approach effectively involves three equations ((10), (11), and (12)), the estimated standard errors in the updating equation in (12) are potentially misleading. We bootstrap the standard errors to remedy this problem. We likewise use bootstrapping to compute bias reduction estimates of the coefficients in (12).

Indirect Approach: The reduced-form indirect approach is less elegant, but less restrictive. The intuition of this approach (see equation (9)) is relatively simple: after controlling for relevant household and village characteristics, systematic updating implies that the distance between an individual's observed rainfall prediction and that of the DMC should be smaller for those receiving and believing the DMC forecast. The household and village vectors here are similar to those in the selection and outcome equations ((11) and (10), respectively) of the direct approach. We specify equation (9) of the indirect approach as:

$$\begin{aligned} \left|d_{ij}^s\right| &= \beta_0 + \beta_1 MALE_{ij} + \beta_2 AGE_{ij} + \beta_3 AGE_{ij}^2 + \beta_4 CULT_{ij} + \beta_5 TLU_{ij} + \beta_6 TLU^2{}_{ij} \\ &+ \beta_7 KENYA_j + \beta_8 FURMAT_j \\ &+ \beta_9 RC_{ij} + \beta_{10} GOOD_{ij}^s + \beta_{11} GOOD^{[+]s}{}_{ij} + \varepsilon_{ij}^s \end{aligned} \tag{13}$$

where $GOOD_{ij}^s$ is the interaction variable $(\overline{d_{-DMC,j}^s} \times RC_{ij})$ defined in (9a), which proxies for how 'good' or 'bad' the DMC forecast was considered by those in village j who received and believed it, and

$$GOOD^{[+]s}{}_{ij} = \begin{cases} GOOD_{ij}^s & if\ GOOD_{ij}^s \geq 0 \\ 0 & if\ GOOD_{ij}^s < 0 \end{cases}$$

Note that this specification hinges on d_{ij}^s being measured as an absolute value. Without the absolute value operator, the interaction term may simply capture cross-village differences in mean rainfall beliefs since the DMC issued only two different forecasts for our study area. With the absolute value operator, this interaction term can effectively isolate updating asymmetries. In (13), s={A, B} and ε_{ij}^s is a random error term with $\varepsilon^A \neq \varepsilon^B$ and $\sigma^{AB}=Cov(\varepsilon^A, \varepsilon^B) \neq 0$.

Since $|d_{ij}^A|=|d_{ij}^B|=0$ indicates that individual i in village j has climate beliefs that correspond perfectly to the DMC forecast, a negative coefficient on an explanatory variable in (13) indicates that an individual's rainfall belief converges to the DMC forecast as the variable increases. The coefficients of primary interest are β_9, β_{10}, and β_{11}. β_9 is an indirect updating coefficient indicating whether those

[23] 5 (52) and 16 (0) observations are lower- and upper-censored, respectively, for s=A (s=B).

receiving and believing the DMC forecast update their climate priors in response to receiving and having confidence in the external forecast irrespective of the direction and distance between the external and local prior forecast. $\beta_9<0$ would imply that, controlling for other factors, forecast recipients indeed update their beliefs in the direction of the DMC forecasts. β_{10} indicates whether forecast recipients assimilate good forecasts differently than bad ones. With $GOOD_{ij}^{s}$ defined in (9a), $\beta_{10}<0$ would imply that good forecasts are assimilated more readily than bad ones. Finally, β_{11} is a switching coefficient that allows $GOOD_{ij}^{s}$ to have a different slope in the positive domain than in the negative domain. Thus, $\beta_{10}+\beta_{11}$ is the total updating effect of $GOOD_{ij}^{s}$ when this variable is positive, and β_{10} is the total updating effect of $GOOD_{ij}^{s}$ when it is negative. Relevant null hypotheses for these coefficients are therefore

$H4_o$: $\beta_9=0$ $H4_A$: $\beta_9<0$

$H5_o$: $\beta_{10}=0$ $H5_A$: $\beta_{10}>0$

$H6_o$: $\beta_{10}+\beta_{11}=0$ $H6_A$: $\beta_{10}+\beta_{11}<0$

$H7_o$: $\beta_9=0$ and $\beta_{10}+\beta_{11}=-1$ $H7_A$: $\beta_9\neq 0$ or $\beta_{10}+\beta_{11}\neq -1$

Rejection of the H4, H5 and H6 null indicates that updating occurs in response to external forecast information. Rejection of the H5 (H6) null indicates that pastoralists update in response to pessimistic (optimistic) external forecasts. Rejection of the H6 null suggests that updating asymmetrically favors good news over bad. Failure to reject the H7 null would signal that optimistic forecasts are accepted as objective probabilities.

A further insight into pastoralists' cognitive processing of information can be gleaned from β_8, the coefficient on FURMAT. The early atypical *furmat* rains in two of the Kenyan villages may have induced significant optimism. Among respondents who experienced *furmat* rains, forecasts recipients offered extreme optimistic (degenerative) forecasts with the same frequency as their less informed neighbors, suggesting that these cognitive effects may indeed dominate any updating that might otherwise occur. In this specification, this can be tested with the hypothesis:

$H8_o$: $\beta_8=0$ $H8_A$: $\beta_8>0$ for s=A

Interpreting the result of this null requires an understanding of the historical correlation between *furmat* rains and the long rains, which we explore in the next section. Rejection of the H8 null when the correlation between the *furmat* and long rains is significantly positive would suggest that any induced optimism is justified. In such a case pastoralists may be sequentially updating their beliefs, first, in response to the signal provided by the *furmat* rains and, second, to the DMC forecast. Rejection of this null when there is no statistical correlation, or when there is a significantly negative correlation, would suggest that pastoralists are systematically (over-)optimistic in their interpretation of *furmat* rains.

The remaining variables in (13) control for other factors that may affect an individual's processing of information and formulation of expectations. None of the individual or village characteristics are interacted with RC_{ij}, therefore corresponding coefficients do not represent marginal effects on the processing of the DMC forecast. Rather, these coefficients indicate how individual and household characteristics affect the proximity of an individual's priors to the DMC forecast. Gender, education and age may affect how an individual predicts seasonal precipitation as discussed in the previous section. Once a household that cultivates makes production decisions it cannot move its crops to areas with more rainfall if its climate expectations turn out to be wrong. A purely pastoralist household, on the other hand, can and does move its animals if rainfall is lower than expected. Hence, as discussed in section III, accurate precipitation predictions are relatively more valuable to households that cultivate, and one would expect such households to formulate their beliefs relatively more carefully. β_4 should therefore be negative.

Since the herd size held by a household is a strong correlate of wealth and wealthy households are better able to cope with climate shocks, one might expect such households to care relatively less about accurate rainfall predictions. Furthermore, households with more livestock are likely to be more pastoralism-oriented and thus more mobile in responding to rainfall shortages, a further reason to expect $\beta_5>0$. Conversely, there are legitimate reasons to expect $\beta_5<0$. Wealth may be correlated with latent characteristics that affect cognitive processing of information. Wealthy households could be wealthy precisely because they are, on average, relatively good at assessing and strategically responding to information. Wealthy households may also have access to broader networks of information. A priori expectations on the TLU coefficients are therefore ambiguous.

The village variable KENYA is expected to improve individuals' forecast accuracy. Relative to Ethiopia, Kenya has better infrastructure, including education and health care, which may help individuals formulate more accurate rainfall predictions. Because Kenya has better infrastructure, access to DMC forecasts may be easier. We therefore expect this variable to affect RC_{ij} more directly than $|d_{ij}^s|$.

The econometric issues involved with the indirect approach are comparable to those of the direct approach that were previously discussed.[24] As before, the dependent variables in (13) has distinctly discrete properties. Indeed, in our data $|d_{ij}^A|$ and $|d_{ij}^B|$ take on only 17 and 14 different values, respectively. We therefore allow for heteroscedasticity in estimating equation (13). Secondly,

[24] Moreover, the previous footnote about SUR is also relevant for the indirect approach. Since $GOOD_{ij}^s$ is the only variable that distinguishes s=A from s=B in equation (13) and SUR efficiency gains are zero when independent

$|d_{ij}^s|$ is potentially lower-censored at 0 and upper-censored at $(1-\pi_{DMC,j}^s)$.[25] Very few of our observations on $|d_{ij}^s|$ are actually censored, however, which makes the benefits to Tobit estimation trivial compared to its limitations. We therefore choose to use standard OLS techniques when estimating equation (13). We bootstrap to compute bias reduction estimates of the coefficients in (13).

C. Results

The estimates of the selection model and the direct updating equation are reported in Table 1. The selection equation has $(1-RC_{ij})$ as the dependent variable since it is those with $RC_{ij}=1$ for whom prior beliefs are unobserved. In recognition of possible censored data problems – although the degree of censoring is not extreme – we estimate the updating equation using both OLS and Tobit[26] techniques. These results, shown in Table 2, indicate strong updating of seasonal rainfall expectations. For both the above and below normal forecast probabilities, the point estimates on δ_1 are mechanically constrained at a value of 1.0, so one cannot reject the null that $\delta_1=1$ at any reasonable significance level. Of greater interest, the estimated coefficients on (d x RC) are negative for both above and below normal states. These coefficients are significantly less than -1.0 for both states and for both OLS and Tobit estimation, suggesting that pastoralists may even 'over-adjust' their expectations in response to the DMC forecast. We easily reject the null hypothesis of perfect updating at the five percent level in favor of an over-adjusting alternative. In spite of ubiquitous access to and confidence in indigenous climate forecasting traditions, and despite widespread illiteracy and unfamiliarity with computer-based technologies, east African pastoralists appear to update their climate beliefs strongly in response to modern forecasts disseminated from the regional Drought Monitoring Centre. This result is particularly striking given that the DMC forecast to which these pastoralists apparently respond seems rather ambiguous and are at very coarse spatiotemporal scale.

In contrast to the direct estimation approach, which estimates unconditional priors for those receiving and believing the DMC forecast using a selection bias model, the indirect approach relies on a computed 'community consensus' as described in the preceding section. Before reporting the results of the indirect estimation approach and to facilitate the interpretation of these results, it is helpful to

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variables are identical, the efficiency gain of SUR estimation vis-à-vis OLS would therefore be negligible. We therefore choose not to employ simultaneous estimation techniques.

[25] When $\pi_{ij}^s=0$, $|d_{ij}^s|=\pi_{DMC,j}^s$, but since $\pi_{DMC,j}^s< 1-\pi_{DMC,j}^s$ for all s (recall $\pi_{DMC,j}^s<50\%$ for all s) and the difference is measured as an absolute value, $\pi_{DMC,j}^s$ cannot be a censoring point.

[26] Estimating the updating equation as a Tobit model requires an assumption about the distribution of the residuals (assumed to be normally distributed in this case), and heterosceadasticity must be modeled as structural, in this case using a multiplicative form, $\sigma_i = \sigma e^{\underline{\gamma' z_i}}$, where z_i included ROAD, TLU, EDU, and KENYA. We found the parameter

discuss explicitly these community consensus measures and the $GOOD_{ij}^{s}$ variable that they construct in conjunction with the village-specific DMC forecast and RC_{ij} variable (recall equations (9) and (9a)). Table 3 reports these village-level variables along with the percent receiving and believing the DMC forecast. Note the geographic unevenness of receipt and confidence in the DMC forecast. Table 3 also shows that while the estimated community consensus varies considerably between villages across both above normal (A) and below normal (B) states, the standard errors of these estimated means suggest that respondents with $RC_{ij}=0$ offered similar forecasts. The precision of these estimates, which indicates that the forecasts of respondents with $RC_{ij}=0$ are clustered closely together within each village, seems to validate both the existence of a community consensus and the approximation of this consensus using the mean village forecast conditional on $RC_{ij}=0$. The final two columns in Table 3 indicate that the DMC forecast for s=B was uniformly received as bad news. Consequently, we can only estimate the switching coefficient on $GOOD^{[+]}{}_{ij}^{s}$ for s=A. Note that in Wachille for s=A (8 respondents with $RC_{ij}=1$) and Dirib Gumbo for s=A,B (1 respondent with $RC_{ij}=1$) this external forecast was essentially neutral (i.e., it mimicked the corresponding community consensus).

The results from the indirect approach, reported in Table 4, reinforce the findings of the direct approach and provide an additional insight concerning asymmetric updating. The coefficient estimate on the *furmat* dummy variable is positive and significant for s=A. [27] Having rejected the null that this coefficient is zero, we must first estimate the correlation between *furmat* and long rains before interpreting this result. Using monthly rainfall data for North Horr (1977-2001) – a period that includes seven *furmat* episodes – a simple univariate regression of long rains as a function of *furmat* rains yields a statistically insignificant correlation of -0.28 (std. error = 0.38). Thus, atypical *furmat* rains, while increasing available forage, appear to communicate no meaningful information about the rainfall of the subsequent long rains season and certainly not information that the long rains are likely to be greater in volume. This, combined with the significant and positive coefficient on FURMAT, suggests that pastoralists who experienced *furmat* rains were not updating in response to an additional, natural signal received in the form of early rains. Rather, they may have optimistically interpreted a statistically

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estimates under the Tobit model to be sensitive to assumptions about the underlying error distribution and the specification of the conditional variance equation. So we place greater confidence in the OLS results.

[27] Since the dependent variable in the indirect approach is the *absolute value* of d_{ij}^{s}, one cannot in fact tell whether a positive coefficient indicates optimism, pessimism, or simply a mixture of extreme deviations from the DMC forecast. To settle the matter, we conducted an additional regression of the indirect approach specification where the dependent variable was d_{ij}^{s}, instead of its absolute value. From this estimation it is clear that the coefficient on the *furmat* dummy in Table 5 indeed implies optimism, not pessimism.

uninformative signal.[28] Alternatively, instead of offering an estimate of their rainfall beliefs, they may have offered an estimate of the probability their utility from rainfall would be above or below normal. In either case, the pastoralists who observed *furmat* rains seem to be more optimistic than those who did not. This relative optimism may be very well justified as *furmat* rains guarantee better pasture in the near term, thereby decreasing the likelihood of catastrophic livestock mortality and household welfare losses. With their systematic optimism, these pastoralists seem to share certain cognitive biases with financial analysts and stockbrokers worldwide (Easterwood and Nutt 1999, Hirshleifer and Shumway 2003).

Those who receive and have confidence in external forecasts indeed appear to update their priors in the direction of the DMC prediction when it places a higher probability on a more desirable outcome than did the subject's prior beliefs. The estimated coefficients on GOOD are uniformly negative and significant. Recall that the GOOD variable in the indirect method permits identification of asymmetries of the updating process introduced by whether the DMC forecast was received as good or bad news. We find consistent evidence against the null of symmetric updating and in favor of the alternate hypothesis that pastoralists assimilate relatively good forecasts about the most desirable state of nature (above normal rainfall) more completely than relatively bad forecasts or even relatively good ones about the least desired state of nature (below normal rainfall). Because the information contained in the DMC forecast is non-rival, it is possible, even probable, that those receiving the forecast share this information with their neighbors, in which case $\overline{d^{s}_{-DMC,j}}$ would be underestimated and the GOOD variable would be uniformly understated. There is thus good reason to believe that the asymmetric updating effect is actually stronger than we have estimated it to be. In short, climate forecast information seems to have both sign and magnitude effects on respondents' belief updating processes.

A few other results from Table 6 warrant comment. First, age does not appear to matter to one's updating patterns once one controls for the likelihood of receiving and having confidence in external forecasts, which is affected by age, as shown in Table 1. Perhaps surprisingly, livestock wealth appears uncorrelated with updating patterns. Wealth may not be attributable to more skillful management of information, in which case we would expect to find a significant, negative correlation between the updating distance measure and wealth. Finally, respondents who cultivate crops evince subjective climate probabilities that are considerably closer to those of the DMC than do pure pastoralists. This may be partly due to both cultivation and meteorological stations being more

[28] These pastoralists can hardly be blamed for perceiving a correlation where none exists as this is one of the most robust flaws in human reasoning (Nisbett and Ross 1980).

prevalent in relatively wet areas (Smith, et al. 2001). This is consistent with other evidence that climate forecasting is perhaps better suited to crop producers than extensive livestock herders in the developing world (Luseno, et al. 2003).

V. 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. 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 poverty alleviation grow rapidly in importance. Widespread optimism about climate forecasting's potential as a development tool implicitly depends, however, on previously untested assumptions that intended beneficiaries both receive and have confidence in external forecasts, and that they update prior beliefs in response to this information. Yet in cultures that have long used indigenous forecasting methods and where access to modern media and familiarity with computer-based technologies are limited, one might suspect that new forecasts generated and disseminated by outsiders using incomprehensible computer models may not readily gain the acceptance necessary to induce behavioral change.

This paper presents the first direct study of these issues, exploring how the subjective rainfall probability distributions of poor pastoralists in southern Ethiopia and northern Kenya change in response to receipt of modern, computer-generated climate forecasts. Limited access to modern media (e.g., radio, television, newspapers) and the existence of a suite of established, indigenous forecasting methods accessed by virtually all pastoralists leave little space for adoption of external climate forecasts among east African herders. Only 13.7 percent of our respondents both received and expressed confidence in computer-based climate forecasts, although one might reasonably predict greater future use as radio availability increases and this information becomes more familiar.

Perhaps the trickier question is whether those who receive external climate forecast information really use it. Somewhat surprisingly, we find that, on average, those receiving and believing computer-based forecasts vigorously update their above normal seasonal rainfall expectations in the direction of the modern forecast. Under some specifications, one cannot even reject the null that they adopt the external climate forecast completely, as an objective probability, or even "overshoot" in their adjustment. An asymmetry is apparent in pastoralists' response being especially strong when the external forecasts suggest a greater likelihood of a favorable (wetter) season or, to a slightly lesser degree, a lower likelihood of an unfavorable (drier) season than they had previously believed. Furthermore, those in locations where they have recently observed unusual early rains, which are historically uncorrelated with the more important long rains, formulate relatively more optimistic (higher) expectations for continued above normal rainfall. These results suggest a systematic optimism manifest in updating processes that differ according to the direction in which one is led to revise prior beliefs. East African pastoralists appear remarkably similar to financial analysts on Wall Street in their tendency to overreact to good news, underreact to bad news and to interpret genuinely ambiguous information optimistically (Easterwood and Nutt 1999). These general findings are robust to a variety of different estimation methods meant to address various econometric complications.

Our conclusion that pastoralists update their climate expectations, albeit with a cognitive bias towards optimism, suggests that these same pastoralists appear to place little value on modern climate forecasts (Luseno, et al. 2003) not because they are unable to process the information and adjust their expectations accordingly, but precisely because they have at their disposal *ex post* options for responding to climate shocks. Once new information is in hand, in the form of the DMC forecast for example, updating beliefs is costless. Thus, even pastoralists who seemingly have no intention of using the information to formulate better livelihood strategies, update their expectations accordingly. Even if not directly beneficial, updating is difficult to resist, as is doing so optimistically.

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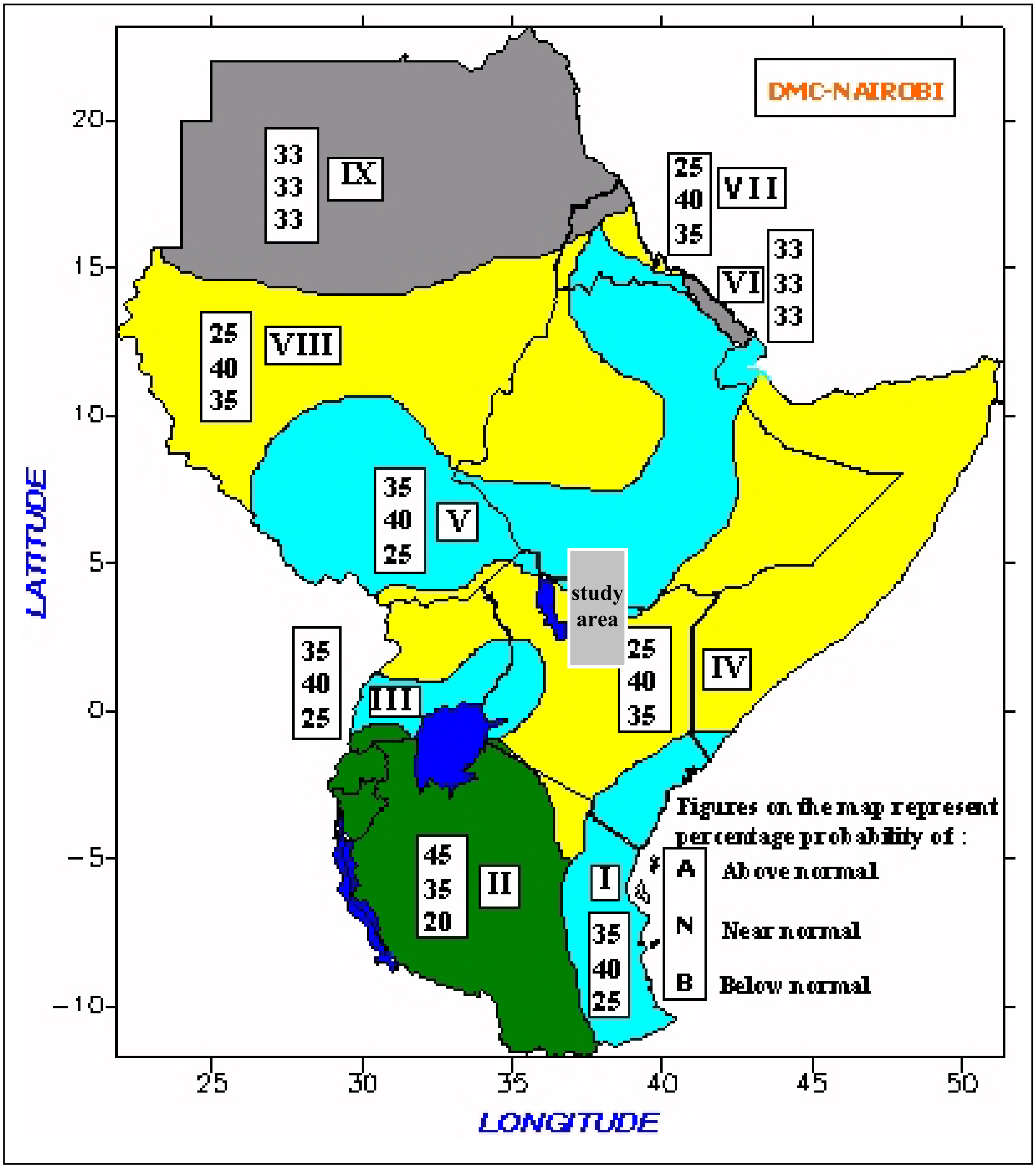

Figure 1 DMC forecast for the 'long rains' season (March-May) 2001

Table 1 Selection model results estimated using Heckman's technique (dependent variables in outcome equation measured as a percentage; Standard errors in parentheses; * (**) indicates statistical significance at the 10% (5%) level.)

	Selection Equation	Outcome Equation	
		s=A	s=B
Dependent Variable	(1 - RC)	π^A	π^B
Intercept	1.10	31.54 *	42.87 **
	(0.868)	(19.6)	(18.6)
Male {0,1}	-0.081	3.43	-5.11 **
	(0.278)	(3.51)	(2.73)
Education (yrs)	-0.13 **	-1.34	0.23
	(0.044)	(2.29)	(1.50)
Age	0.047	-0.42	-0.18
	(0.037)	(0.737)	(0.674)
Age^2 (÷100)	-0.049	0.19	0.27
	(0.038)	(0.701)	(0.607)
Cultivation {0,1}	0.49 *	9.00 *	-1.46
	(0.263)	(5.48)	(3.93)
Livestock (TLU)	-0.004	-0.13 *	0.16 **
	(0.006)	(0.081)	(0.063)
Radio {0,1}	-0.36	11.78 **	0.79
	(0.285)	(6.35)	(4.75)
Furmat {0,1}		30.16 **	-16.51 **
		(5.51)	(4.26)
Kenya {0,1}	-0.17		
	(0.286)		
Road {0,1}	-0.98 **	5.52	-19.51 **
	(0.328)	(8.07)	(5.70)
Lambda		12.35	-2.57
		(34.5)	(24.0)
Rsq		0.22	0.25
N	244	214	214

Table 2 Coefficients for the direct approach to estimating the updating equation with heteroskedasticity-consistent standard errors (dependent variable, $d_{ij/DMC}^{s}$, measured as a percentage; Standard errors in parentheses; * (**) indicates statistical significance at the 10% (5%) level.)

Variable	Above normal rainfall forecast		Below normal rainfall forecast	
% Censored (lower; upper)	(0 ; 6%)		(19% ; 0)	
	OLS†	Tobit	OLS†	Tobit
d_{ij}^{s}	1.00 **	1.04 **	1.00 **	1.00 **
	(1.59E-17)	(0.064)	(1.52E-17)	(0.005)
d_{ij}^{s} x (RC_{ij})	-1.72 **	-1.83 **	-1.31 **	-1.27 **
	(0.185)	(0.073)	(0.035)	(0.005)
Adj-R^2	0.85		0.95	
Breusch-Pagan (d.f.=1)	108.6		763.2	

† Coefficients are bootstrap-bias reduction estimates and standard errors are bootstrapped.

Table 3 Percent receiving and believing the DMC forecast, and 'Community Consensus' and $GOOD_{ij}^{s}$ calculations by village.

		Communmity Consensus (%)	(std.error)			$GOOD_{ij}^{s}$ for RC_{ij}=1	
	% RC_{ij}=1	Forecast of Above normal rainfall (s=A)		Forecast of Below normal rainfall (s=B)		s=A	s=B
ETHIOPIA							
Dida Hara	0%	26.4	(2.1)	22.5	(3.0)	8.6	-2.5
Dillo	0%	14.7	(0.8)	57.1	(2.0)	20.3	32.1
Finchawa	4%	20.8	(1.7)	6.6	(0.7)	14.2	-18.4
Wachile	30%	35.1	(5.5)	12.7	(2.6)	-0.1	-12.3
KENYA							
Dirib Gumbo	4%	25.3	(3.1)	35.0	(3.8)	-0.3	0.0
Kargi	5%	34.1	(5.8)	27.7	(4.9)	-9.1	-7.3
Logologo	27%	12.0	(1.3)	22.9	(3.1)	13.0	-12.1
Ngambo	22%	47.0	(4.0)	14.8	(2.0)	-22.0	-20.2
North Horr	8%	57.3	(7.8)	12.3	(3.1)	-32.3	-22.7
Suguta Marmar	23%	60.8	(5.7)	12.7	(3.9)	-35.8	-22.3
		Of respondents with RC_{ij}=1:					
					number receiving the DMC forecast as 'good' news	7	0
					number receiving the DMC forecast as 'bad' news	23	29

Table 4 OLS bootstrap-bias reduction coefficients for the indirect approach with heteroskedasticity-consistent standard errors (dependent variable is $|d_{ij/DMC}{}^{s}|$, measured as a percentage; Standard errors in parentheses; * (**) indicates statistical significance at the 10% (5%) level.)

	Above normal rainfall forecast	Below normal rainfall forecast
% Censored (lower; upper)	(2%; 0)	(6%; 0)
Intercept	23.2 **	22.2 **
	(10.0)	(7.6)
Male {0,1}	2.66	-0.76
	(2.3)	(1.7)
Age	-0.33	-0.18
	(0.35)	(0.31)
Age^2 (÷100)	0.34	0.25
	(0.31)	(0.29)
Cultivation {0,1}	-1.10	-0.81
	(2.3)	(1.7)
Livestock (TLU)	-0.010	-0.016
	(0.086)	(0.086)
$Livestock^2$ (÷100)	0.002	0.030
	(0.049)	(0.046)
Kenya {0,1}	2.93	-0.58
	(2.3)	(1.7)
Furmat {0,1}	10.4 **	2.5
	(5.0)	(2.7)
RC_{ij}	9.9 *	-7.3
	(5.7)	(8.7)
$GOOD_{ij}^{s}$	-0.41 *	-0.69 *
	(0.22)	(0.49)
$GOOD^{[+]}{}_{ij}^{s}$	-0.99 *	
	(0.61)	
Breusch-Pagan (d.f.=11,10)	152	13.2