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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. Recent advances in model-based climate forecasting have expanded the range, timeliness and accuracy of forecasts available to decision-makers whose welfare depends on stochastic climate outcomes. There has consequently been considerable recent investment in improved climate forecasting for the developing world. Yet, in cultures that have long used indigenous climate forecasting methods, forecasts generated and disseminated by outsiders using unfamiliar methods may not readily gain the acceptance necessary to induce behavioral change. The value of model-based climate forecasts depends critically on the premise that forecast recipients actually use external forecast information to update their rainfall expectations. We test this premise using unique survey data from pastoralists and agropastoralists in southern Ethiopia and northern Kenya, specifying and estimating a model of herders updating seasonal rainfall beliefs. We find that those who receive and believe model-based seasonal climate forecasts indeed update their priors in the direction of the forecast received, assimilating optimistic forecasts more readily than pessimistic forecasts.

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 (Rosenzweig and Binswanger 1993) it may pay to have timely, reliable climate forecasts to help people choose optimal state-contingent livelihood strategies, both to evade disaster and to capitalize on temporary, favorable states of nature. Recognizing the value seasonal climate forecasts could have to subsistence farmers and pastoralists¹ living in the arid and semi-arid lands (ASAL) of Sub-Saharan Africa (SSA) and elsewhere, several development agencies have directed much attention and funding to establishing Famine Early Warning Systems (FEWS) over the past two decades (Walker 1989, Barrett 2002). 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, locals must update their prior climate beliefs in response to external forecasts.

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.

- (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 (Folland et al. 1991, Hulme et al. 1992a, 1992b, Beltrando and Camberlin 1993, Cane et al. 1994, Ogallo 1994, Barnston et al. 1996, Agatsiva 1997). A companion paper (Luseno, et al. forthcoming) explores the complex issues surrounding (iv) for the pastoralist populations we study here. In the present paper, we restrict our attention to core questions (ii) and (iii), estimating who receives and believes climate forecast information, whether receipt and confidence in such forecasts changes their beliefs about uncertain future states of nature and, if so, how, using a unique data set collected among pastoralists and agropastoralists in southern Ethiopia and northern Kenya. These peoples are extraordinarily poor and vulnerable to regular, severe climate shocks, as the international media has vividly communicated during repeated horrific droughts in recent years.

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. Using a unique data set, 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. 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. Beliefs Updating in the Literature

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 deemed, thereby generating a new, posterior subjective probability distribution, presumably following a Bayesian mechanism.² Cognitive psychologists point out that the ‘strength’ or ‘extremeness’ and the ‘credibility’ of the information enter importantly into the process of updating beliefs, typically with a predictable bias towards the former (Griffin and Tversky 1992, Tversky and Kahneman 1974). 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, p.5 hereafter HR) ask the questions, ‘suppose there exists an option of getting additional information, how should an individual decide whether to get this information and, should she decide to get it, how much information to collect?’ and ‘how do such ‘information actions’ affect market equilibria?’ They attempt to answer these questions by formulating a model in

² Heuristically, Tversky and Kahneman (1974) represent this process of formulating priors and then adjusting to additional information as an ‘anchoring-and-adjustment’ model.

which there are a number of possible future states ($s=1,\dots,S$) and several actions ($x=1,\dots,X$) that might be taken by an individual. An action must be chosen *before* the future state is known and has an outcome of c_{xs} *after* the state is observed. The individual begins with an unconditional prior probability distribution of possible states of nature occurring, denoted π_s , but has the option of seeking additional information to help refine π_s . Additional information comes in the form of messages ($m=1,\dots,M$), each with q_m , an unconditional probability of being received. From the individual's perspective, the potential value of receiving a message is based not on the message *per se* but on an accompanying joint probability matrix, which gives j_{sm} , the joint probability of observing state s given message m is received. Provided the individual has confidence in both the message received and the associated j_{sm} , she can update her unconditional prior beliefs according to Bayes'

Theorem. Her updated posterior beliefs therefore become $\pi_{s/m} \equiv \frac{j_{sm}}{q_m}$. Defining $q_{m/s} \equiv \frac{j_{sm}}{\pi_s}$ as the conditional likelihood (probability) of receiving message m given that state s obtains, we have

$$(1) \quad \pi_{s/m} \equiv \frac{j_{sm}}{q_m} \equiv \pi_s \frac{q_{m/s}}{q_m}$$

where $\frac{q_{m/s}}{q_m}$ represents an updating factor dictating in which direction and how much to change the unconditional prior probability upon receiving message m .

HR derive from this abstract formulation three “useful propositions” that are relevant to the present paper. 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. HR point out that this confidence is expressed statistically in the “tightness” of the prior probability distribution, i.e., by dispersion around the mean. Second, the greater the confidence of the message (i.e., the tighter the

distribution of $q_{m/s}$) the greater its effect on the individual's posterior probability distribution. Third, the more 'surprising' a message, measured by how different it is from the individual's prior beliefs, the greater the updating effect.

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. Rabin (1998) presents an excellent survey of the intersection of psychological research and economics, including the relevant topics of belief perseverance and confirmation bias. The general aim of research related to these topics is to assess the effect of existing beliefs on the interpretation of new information. It seems existing or initial beliefs tend to "anchor" one's processing of new information in relatively predictable ways (Bruner and Potter 1964, Tversky and Kahneman 1974, Tversky and Kahneman 1982). 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).³ In struggling to reconcile existing beliefs with new information, people therefore 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). Further evidence suggests that these cognitive biases become especially pronounced when the 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 (i.e., 'motivated interpretation' (Hales 2002)) Specifically, while 'preference-consistent' information is taken at face value, 'preference-inconsistent' information is processed subjectively and resulting forecasts become biased and dispersed (Hales 2002).

Analysis of non-experimental data tends generally to corroborate the conclusions of the experimental literature. A couple of empirical analyses that seek to understand the cognitive processing of risk are especially relevant. Slovic (1987) examines how people process information about chemical and nuclear technologies and how they use this information to formulate notions of risk. He concludes that while experts employ sophisticated risk assessment tools to evaluate hazards, most everyone else relies on intuitive risk judgments. This intuition, often called risk perception, is based largely on the mishaps and threats that are documented in the popular media. Noting experts' common frustration with citizens' inability to process new information correctly and update their perceptions of risk appropriately, Slovic points out that disagreements about risk should not be expected to vanish when credible evidence is presented since strongly-held prior beliefs resist change because they affect the way subsequent information is processed, a validation of HR's first proposition. Slovic concludes that risk communication and management are bound to fail if they are not structured as a two-way process in which both the public and the experts engage in a dialogue. This observation is directly relevant to contemporary, largely top-down efforts to anticipate climate shocks in marginal areas of the developing world.

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.

Some studies have shown that people rarely update their beliefs in predictable ways. In studies of the challenges of communicating to homeowners the risks associated with radon, 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). Apparently, few homeowners updated their beliefs about radon risks substantially enough to motivate an observable response. Radon presents an invisible and unfamiliar risk to most homeowners, however, and other studies find that when experts are involved, the processing of information and the updating of beliefs conforms more closely to Bayes' Theorem.

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.⁴ Even if experts apparently update their beliefs in a Bayesian manner, they are still subject to complex human emotions and cognitive limitations. One recent study finds, for example, that sunshine is significantly correlated with daily stock returns (Hirshleifer and Shumway 2001). Even experts' processing of information is not immune to feeling a bit more optimistic on sunny days, or rainy days if it is rain that is hoped for. Earlier studies indicate that even experts often misperceive short random sequences as representative of their generating processes—

⁴ 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

e.g., ‘the hot hand’ or ‘belief in the law of small numbers’ (Gilovich, et al. 1985, Tversky and Kahneman 1971).

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 an econometric approach to test whether locals who receive external climate forecasts update their climate expectations in predictable ways. 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 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 ($\underline{y} = 1, \dots, \underline{Y}$). The outcomes (C_{ys}) of these strategies and states of nature can be described by a results matrix as follows:

al. 1989)). In contrast, climate outcomes are purely exogenous to others’ forecasts of them and are therefore not subject to this ‘curse’.

		States (s)		
		A	N	B
Strategies (y)	<u>1</u>	C_{1A}	C_{1N}	C_{1B}
	<u>2</u>	C_{2A}	C_{2N}	C_{2B}
	\vdots	\vdots	\vdots	\vdots
	<u>Y</u>	C_{YA}	C_{YN}	C_{YB}

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. The value of updating beliefs lies in the variability of outcomes conditional on realized states of nature and the correlation between forecast messages and states of nature. If one strategy is optimal regardless of the state of nature or if the forecast message is uncorrelated with observed states of nature, the decision-taker 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. Note, however, that the value of updating one's beliefs 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. For subpopulations with few options available to them – like the pastoralists of southern Ethiopia and northern Kenya who we study – one might therefore expect to find little updating of prior beliefs.

Let the unconditional prior beliefs of individual i in village j be $\pi_{ij}^A, \pi_{ij}^N, \pi_{ij}^B$ 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 forecaster⁵ 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.⁶ 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. forthcoming), so we treat these as a common, location specific component to each individual's prior.

In contrast to HR's framework in which the individual receives a message and an accompanying joint-probability matrix, when an individual receives an external climate forecast she is not receiving a 'message' in the HR-sense, but rather a directly comparable set of external forecast probabilities.⁷ If she has complete confidence in the validity of this external forecast, she considers these objective probabilities, meaning she updates completely and immediately, replacing her priors with this new set of probabilities. Otherwise, she treats the external forecast as a competing subjective probability distribution that must be reconciled with her prior beliefs. Thus, the updating equation that determines her posterior beliefs is somewhat different than in (1) and is given by

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

⁵ 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.

⁶ 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.

⁷ In the literature on Bayesian updating, confidence in these competing probabilities is represented as a variance that the individual assigns to the source. Updating then occurs according to inverse variance weights (i.e., the lower the variance assigned to a source, the more confidence and the larger the updating weight.)

where $\pi_{DMC,j}^s$ is the external forecast probability for state s and $s = \{A, N, B\}$. We use the DMC subscript here because in the Horn of Africa external climate forecasts are released by the Drought Monitoring Centre (DMC), based in Nairobi, and then disseminated through national meteorological agencies. This updating equation in (2) 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} , which can be interpreted as an updating weight representing the individual's willingness to abandon her own prior in favor of the DMC forecast probability. Note that (2) can be rearranged to express the posterior probability as a simple linear combination of the prior probability and the DMC's forecasted probability. 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.

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 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 $\pi_{DMC,j}^s$ 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

$$(4) \quad \pi_{ij|DMC}^s = \pi_{ij}^s [1 - RC_{ij} \delta_{ij}] + \pi_{DMC,j}^s [RC_{ij} \delta_{ij}]$$

where $RC_{ij}=1$ if individual i in village j receives and has confidence in the DMC forecast and $RC_{ij}=0$ otherwise. When $\delta_{ij}=1$ 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 $\pi_{DMC,j}^s$ from both sides, the updating equation in (4) can be further simplified to

$$(5) \quad d_{ij|DMC}^s = d_{ij}^s - d_{ij}^s RC_{ij} \delta_{ij}$$

where $d_{ij}^s = (\pi_{ij}^s - \pi_{DMC,j}^s)$ and $d_{ij|DMC}^s = (\pi_{ij|DMC}^s - \pi_{DMC,j}^s)$. In section IV we estimate this conditional difference in respondents' probability distributions over climate state.

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 should 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.

In summary, individual i 's prior, π_{ij}^s , can 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:⁸

$$(6) \quad \pi_{ij}^s = f^s(\underline{x}_{ij}, \underline{z}_j, \epsilon_{ij}^f)$$

⁸ 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, where we indeed find evidence of asymmetric updating.

The prior belief defined in (6) provides the individual with a baseline which she can adjust according to the updating equation in (5).

B. Econometric Approaches to Estimating Updating

There are two econometric approaches worth considering when trying to understand the degree to which pastoralists update their climate beliefs. A *direct approach* involves directly recovering π_{ij}^s for individuals who *do* receive and believe the DMC forecast.⁹ This requires an explicit model of π_{ij}^s , but enables one to estimate (5) directly. The coefficient on the interaction term in such estimation represents the mean updating weight implied by the data. An alternative, *indirect approach* does not attempt to recover π_{ij}^s and instead models π_{ij}^s implicitly. This approach does not permit direct estimation of the updating equation in (5), but allows for a broader investigation into the factors that affect the belief updating process. Both approaches will be estimated in section IV.

Directly recovering π_{ij}^s for individuals receiving and believing the DMC forecast requires an explicit model of π_{ij}^s . Since π_{ij}^s is observed if $RC_{ij}=0$ and is latent otherwise,¹⁰ this can be modeled as a selection bias model where the outcome equation is shown in (6) and the selection equation specifies the factors that affect whether an individual receives and believes the DMC forecast. Household characteristics such as ownership of a radio and education, and village characteristics such as nearness to major roads importantly determine whether an individual receives and believes the DMC forecasts. Thus,

$$(7) \quad RC_{ij} = p(x_{ij}, z_j, \varepsilon_{ij}^p)$$

⁹ Recall that π_{ij}^s is only observable for individuals who either did not receive or did not believe the DMC forecast.

¹⁰ Our data provide only a single belief for each household, expressed as a trinomial probability forecast collected *after* the DMC issued its forecast. Hence we have data on $\pi_{ij|DMC}^s$. When $rc_{ij}=0$, $\pi_{ij}^s = \pi_{ij|DMC}^s$, but whenever $RC_{ij}=1$ and $\delta_{ij}>0$, $\pi_{ij}^s \neq \pi_{ij|DMC}^s$.

Correcting the outcome equation in (6) for this selection bias yields parameter estimates that can be used to estimate $\hat{\pi}_{ij}^s$ 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.

The indirect approach involves an implicit formulation of π_{ij}^s . There are several factors that presumably affect δ_{ij} . Again, individual and village characteristics influence an individual's disposition to assimilate the DMC's forecasts by updating her priors. Thus,

$$(8) \quad \delta_{ij} = h(\underline{x}_{ij}, \underline{z}_j, RC_{ij}, \epsilon_{ij}^h)$$

The indirect approach controls for individual and village characteristics, which affect both the formulation of π_{ij}^s as shown in (6) and an individual's willingness to assimilate the DMC forecast (δ_{ij}) as shown in (8), to ascertain whether d_{ij}^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,

$$(9) \quad \begin{aligned} d_{ij}^s &= g^s(\pi_{ij}^s, \delta_{ij}, v) = g^s(f^s(\underline{x}_{ij}, \underline{z}_j, \epsilon_{ij}^f), h(\underline{x}_{ij}, \underline{z}_j, RC_{ij}, \epsilon_{ij}^h), RC_{ij}, v_{ij}) \\ &= g^s(\underline{x}_{ij}, \underline{z}_j, RC_{ij}, v_{ij}^*) \end{aligned}$$

Since π_{ij}^s is not explicitly recovered for individuals with $RC_{ij}=1$ and the newness of external forecast information affects the updating process, an attempt must be made to generate some proxy for π_{ij}^s .

As presented thus far, d_{ij}^s can be either positive or negative, depending on whether the DMC forecast is more or less favorable than individual i 's observed forecast, which raises the question: are individuals likely to update asymmetrically? Certainly, just as mood affects one's assessment of risk, so too might one systematically react differently to bad news than to good. We 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

$(\pi_{ij}^A > \pi_{DMC,j}^A)$. A recipient may assimilate this ‘bad news’ more or less readily than ‘good news’ that is of a similar distance from her prior belief. That is, surprises should have two important dimensions in updating: magnitude (i.e., distance from prior) and direction (i.e., whether the surprise is good or bad). To account explicitly for potential asymmetries in updating, equation (9) can be modified as

$$(10) \quad |d_{ij}^s| = h^s(\underline{x}_{ij}, \underline{z}_j, RC_{ij}, (\overline{d_{-DMC,j}^s} \times RC_{ij}), \varepsilon_{ij}),$$

where

$$(10a) \quad \begin{aligned} \overline{d_{-DMC,j}^B} &= \left(\frac{1}{n_{-DMC,j}} \sum_{i=1}^{n_{-DMC,j}} (\pi_{ij}^B | RC_{ij} = 0) \right) - \pi_{DMC,j}^B \\ \overline{d_{-DMC,j}^A} &= \pi_{DMC,j}^A - \left(\frac{1}{n_{-DMC,j}} \sum_{i=1}^{n_{-DMC,j}} (\pi_{ij}^A | RC_{ij} = 0) \right) \end{aligned}$$

where $n_{-DMC,j}$ is the number of individuals in village j who did not both receive and believe the DMC forecast, and $\overline{d_{-DMC,j}^s}$ is the difference between the non-DMC-influenced climate consensus in village j and the DMC’s forecast for village j . As defined in (10a) for $s = \{A, B\}$, $\overline{d_{-DMC,j}^s} > 0$ implies that the DMC forecast represents ‘good news’ to those who receive it. The interaction term $(\overline{d_{-DMC,j}^s} \times RC_{ij})$ 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. In effect, this interaction term proxies for the interaction term in (5), with the added advantage of allowing the effect of a surprise on the updating process to be decomposed into a sign effect and a magnitude effect. Note that 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 $\overline{d_{-DMC,j}^s}$ would be underestimated.

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, which typically begin late 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 did the DMC seasonal forecast.

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 modern, computer-based climate forecast information and who expressed confidence in that information.¹¹

¹¹ 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.

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 A, N, or B. Despite the common belief that pastoralists 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., (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).¹² A map of these forecasts is shown in figure 1.

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.¹³ 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 'strength' of the information was

¹² 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.

¹³ By construction, the naïve trinomial forecast is 33-33-33, i.e., not radically different from what DMC broadcast.

low, making a measurable updating effect unlikely (Griffin and Tversky 1992, Tversky and Kahneman 1974).

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.

B. Econometric Models & Issues

Direct Approach: The direct approach hinges on the recovery of respondents' priors, π_{ij}^s , from a selection bias model following Heckman's method. In the outcome equation (6), the vector of individual characteristics, \mathbf{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 AGE²), plus household characteristics such as whether the household cultivates seasonal crops (CULT=1 if cultivates, 0 otherwise),¹⁴ how many tropical livestock units (TLU)¹⁵ are owned by the household and whether the household owns a radio (RADIO=1 if owns radio, 0 otherwise). The vector of village characteristics, \mathbf{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

¹⁴ 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.

¹⁵ One TLU equals 0.7 camels, 1 cattle, or 10 goats or sheep. This is a standard aggregation method.

(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, estimable outcome equation is therefore

$$(11) \quad \pi_{ij}^s = \beta_0 + \beta_1 MALE_{ij} + \beta_2 EDU_{ij} + \beta_3 AGE_{ij} + \beta_4 AGE_{ij}^2 + \beta_5 CULT_{ij} + \beta_6 TLU_{ij} + \beta_7 RADIO_{ij} + \beta_8 FERMAT_j + \beta_9 ROAD_j + \varepsilon_{ij}^f$$

The selection equation in (7) replaces FURMAT with a Kenyan dummy variable (KENYA=1 if the village is in Kenya, 0 if in Ethiopia) and otherwise involves the same explanatory variables:

$$(12) \quad RC_{ij} = \gamma_0 + \gamma_1 MALE_{ij} + \gamma_2 EDU_{ij} + \gamma_3 AGE_{ij} + \gamma_4 AGE_{ij}^2 + \gamma_5 CULT_{ij} + \gamma_6 TLU_{ij} + \gamma_7 RADIO_{ij} + \gamma_8 KENYA_j + \gamma_9 ROAD_j + \varepsilon_{ij}^r$$

The receive-confidence variable (RC) is calculated as a dummy variable that equals 1 if the individual received and expresses confidence in an external forecast provided by the DMC and 0 otherwise.

Once corrected for selection bias, the resulting, consistent estimates of $\underline{\beta}$ can be used to estimate $\hat{\pi}_{ij}^s$ for those whose priors are unobservable ($RC_{ij}=1$). The updating equation in (5) can then be directly estimated as

$$(13) \quad d_{ij|DMC}^s = \delta_1 d_{ij}^s + \delta_2 d_{ij}^s RC_{ij}$$

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 $RC_{ij}=1$.

As mentioned earlier, 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 (5), the null hypotheses of interest here are

$$(14) \quad \begin{aligned} H_o: \delta_1=1, H_A: \delta_1 \neq 1 \\ H_o: \delta_2=0, H_A: \delta_2 < 0 \\ H_o: \delta_2=-1, H_A: \delta_2 \neq -1 \end{aligned}$$

The first null merely reflects the identity between prior and posterior beliefs in the absence of any updating. The second and third hypotheses are our focus, with rejection of the second indicating that updating indeed occurs and failure to reject the third null indicating consistency with a model of complete, immediate updating, wherein the external forecast is accepted as an objective probability.

Indirect Approach: The indirect approach is both less elegant and less restrictive. The intuition behind equation (10) is relatively simple, namely, controlling for relevant household and village characteristics, 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 are as in the selection and outcome equations of the direct approach. We therefore estimate equation (10) as:

$$(15) \quad \begin{aligned} |d_{ij}^s| = & \beta_0 + \beta_1 MALE_{ij} + \beta_2 EDU_{ij} + \beta_3 AGE_{ij} + \beta_4 AGE_{ij}^2 + \beta_5 CULT_{ij} \\ & + \beta_6 TLU_{ij} + \beta_7 TLU_{ij}^2 + \beta_8 RADIO_{ij} + \beta_9 KENYA_j + \beta_{10} FURMAT_j + \beta_{11} ROAD_j \\ & + \beta_{12} RC_{ij} + \beta_{13} GOOD_{ij}^s + \varepsilon_{ij}^s \end{aligned}$$

where $GOOD_{ij}^s$ is the interaction variable $\overline{(d_{-DMC,j}^s \times RC_{ij})}$ defined in (10a) and proxies for how 'good' or 'bad' the DMC forecast was considered by those who received and believed it. In this formulation, as above, $s = \{A, B\}$ and ε_{ij}^s is a random error term with $\varepsilon^A \neq \varepsilon^B$ and $\sigma^{AB} = \text{Cov}(\varepsilon^A, \varepsilon^B) \neq 0$.

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 in (15) indicates that a marginal increase in the corresponding explanatory variable results in relative convergence between the individual's and the DMC's climate prediction. The coefficients of primary interest are β_{12} and β_{13} . β_{12} is an 'updating' coefficient indicating whether those 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. $\beta_{12} < 0$ would imply that, controlling for other factors, forecast recipients indeed update their beliefs in the direction of the DMC forecasts. β_{13} indicates whether those receiving and believing the DMC forecast assimilate ‘good’ news differently than ‘bad’. $\beta_{13} < 0$ would provide evidence that good news is assimilated more readily than bad news since GOOD_{ij}^s as constructed in (10a) is positive (negative) if the DMC is relatively good (bad) news, but zero if $\text{RC}_{ij} = 0$. The marginal effect of receipt and confidence in the external forecast on deviation of the individual’s subjective probability from the external forecast is $\beta_{12} + \beta_{13} \overline{d_{-DMC,j}^s}$. Relevant null hypotheses for these two coefficients are therefore

$$(16) \quad \begin{aligned} H_o: \beta_{12} &= 0, H_A: \beta_{12} < 0 \\ H_o: \beta_{13} &= 0, H_A: \beta_{13} < 0 \\ H_o: \beta_{12} &= 0 \text{ and } \beta_{13} = -1, H_A: \beta_{12} \neq 0 \text{ or } \beta_{13} \neq 0 \end{aligned}$$

Rejection of either of the first two null hypotheses indicates that updating indeed takes place in response to external forecast information. Failure to reject the joint 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_{11} , the coefficient on *FURMAT*. The early atypical *furmat* rains in two of the Kenyan villages may have induced significant optimism, which in this specification can be tested with the null hypothesis:

$$H_o: \beta_{11} = 0, H_A: \beta_{11} > 0 \text{ for } s=A$$

Rejection of this null hypothesis could indicate either a mood effect (Hirshleifer and Shumway 2001) or a belief in ‘the law of small numbers’ (Gilovich, et al. 1985, Tversky and Kahneman 1971).

Among respondents who experienced *furmat* rains, those who received and believed the DMC forecasts 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.

The remaining variables in (7) control for other factors that may affect an individual's processing of information and formulation of expectations. Note that 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, accurate precipitation predictions are relatively more valuable to households that cultivate, and one would expect such households to formulate their beliefs relatively more carefully. B_5 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 $\beta_7 > 0$. Conversely, there are legitimate reasons to expect $\beta_7 < 0$. 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.

Whether an individual possesses a radio directly affects her access to information, including the DMC forecast. Receipt of the DMC forecast is already controlled for elsewhere in the model, but exposure to other forms of information via radio may make an individual better at formulating realistic expectations. Owning a radio is also an expression of a broad willingness to learn and could signal that an individual is proactive in formulating realistic beliefs. Thus, even after controlling directly for receipt and belief in the DMC forecast, owners of radios may more accurately formulate precipitation predictions, reason to expect $\beta_8 < 0$. Note, however, that ownership of a radio should affect RC_{ij} more than formulation of an individual's climate expectations.

The village variables, KENYA and ROAD, are both 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. Living near a main road provides an individual with exposure to a steady stream of external information and should also serve to improve individuals' predictions. Again, however, we expect both to affect RC_{ij} more directly than $|d_{ij}^s|$.

There are several econometric issues that must be addressed before proceeding with the estimation. First, the dependent variables in (13) and (15) have distinctly discrete properties for two reasons. 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 and 23 possible values for $|d_{ij}^s|$ for $s=\{A, B\}$. The observed frequency is zero for several possible values. Thus, $|d_{ij}^A|$ and $|d_{ij}^B|$ take on only 17 and 14 different values, respectively, rather than the 23 possible values shown on the horizontal axis. Estimation should 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.¹⁶

As a second econometric issue, d_{ij}^s and $|d_{ij}^s|$ are potentially doubly-censored. Theoretically, d_{ij}^s is lower-censored at $(-\pi_{DMC,j}^s)$ and upper-censored at $(1-\pi_{DMC,j}^s)$, and $|d_{ij}^s|$ is lower-censored at 0 and upper-censored at $(1-\pi_{DMC,j}^s)$.¹⁷ Estimation of the model in (15) could account for this censored data using Tobit estimation,¹⁸ but this would require an assumption about the distribution of the residuals. In practical terms, 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 in this case, a less restricted correction for heteroscedasticity (e.g., White 1980) is preferable. For d_{ij}^s , the benefits from Tobit estimation, although limited, are more considerable since 5 (52) and 16 (0) observations are lower- and upper-censored, respectively, for $s=A$ ($s=B$).

¹⁶ 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.

¹⁷ 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.

¹⁸ Since the dependent variable in this case, $|d_{ij}^s|$, is treated as cardinal, the degree of censoring should be the only consideration when deciding whether to use Tobit estimation techniques.

Thirdly, it is reasonable to assume that an individual's propensity to update given that she receives the DMC forecast is state-dependent. That is, a risk averse individual may be especially concerned about the possibility that $s=B$ and less concerned about $s=A$. She may therefore process any new information about the probability that $s=B$ more carefully than similar information about $s=A$. Thus, the coefficients in (13) and (15) may be different for $s=B$ than for $s=A$. 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 (Greene 1997) if the independent variables are not identical across equations. In (7), $GOOD_{ij}^s$ is the only variable that distinguishes $s=A$ from $s=B$; the efficiency gain of SUR estimation vis-à-vis OLS would therefore be negligible. 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 for either the direct or the indirect approach.

Finally and importantly, there is a potential cognitive endogeneity problem associated with using RC_{ij} as an independent variable in (13) and (15). While some receive the DMC's forecast through no effort of their own (i.e., exogenously), others actively seek it out. Individuals who intend to use the information to improve their expectations will certainly seek more diligently than those who might consume the DMC forecast only for its entertainment value, rather than for its informational value. The common remedy to endogeneity problems involves instrumental variables. In this case, we generate a proxy by estimating a RC_{ij} -dependent model and using (predicted) propensity scores, RC_{ij}^H , in estimating equations (13) and (15). The equation used to estimate RC_{ij} is identical in specification to the selection equation in (12), but will be estimated differently. The selection model in the direct modeling approach is estimated, using Heckman's technique, as a Probit model. To

generate fitted values of RC_{ij} for use as a proxy, however, the objective is to find the best fit. We therefore use a simple linear probability (OLS) model with heteroscedasticity-corrected standard errors since this generates the best fit and thus estimates predicted values more efficiently than any alternative estimator.¹⁹

Using propensity scores to remedy the endogeneity problem raises additional econometric issues. First, estimated propensity scores (RC_{ij}^H) are imperfect proxies for RC_{ij} and introduce measurement error. One is therefore faced with a tradeoff between the endogeneity bias due to the presence of RC_{ij} and the measurement error due to RC_{ij}^H . The more imperfectly RC_{ij}^H proxies for RC_{ij} , the greater the severity of the measurement error problem and the more relatively attractive the original endogeneity bias. Second, because RC_{ij}^H is a generated regressor, there is additional reason to correct for heteroscedasticity. Third, since the regressors in (12) are nearly identical to those in (15), there are potential multicollinearity problems associated with using RC_{ij}^H , which is essentially a weighted average of several of the regressors already included. To remedy this potential problem, a few of the regressors in (15) can be dropped without affecting the model significantly. Specifically, education, ownership of a radio and proximity to a major road should intuitively enter into the model primarily through RC. Dropping these variables from (15) is thus not too disconcerting.²⁰

C. Results

Table 1 reports the results of the linear probability model for RC that is used to generate propensity scores, RC_{ij}^H . The probability of receiving and having confidence in computer-generated, external

¹⁹ There are two common concerns about the linear probability model. First, the predicted probabilities or propensity scores are not necessarily contained in the range [0,1]. Since the propensity scores in this case are to be used as instruments and not interpreted independently, this is not an issue. Second, errors in (12) are clearly heteroscedastic since RC_{ij} takes on either 0 or 1. This is, however, not a problem provided this heteroscedasticity is corrected in the estimation. We correct for heteroscedasticity following (White 1980)

forecasts is increasing in years of schooling completed and among those who possess a radio or live near a main road, but is decreasing among those who cultivate crops. Note that the fit on this equation is not especially good, with R^2 of just 0.18. This will necessarily hurt the estimation precision of the specifications that include RC_{ij}^H as a generated regressor. Since RC is endogenous in theory, but surely exogenous for some pastoralists, endogeneity bias is quite possibly less problematic than the measurement error introduced by the relatively poor RC_{ij}^H proxy.

The OLS estimates of the direct updating equation, reported in Table 2, corroborate the hypothesis of updating of seasonal rainfall expectations. For both the above and below normal forecast probabilities, the point estimates on δ_1 are very near the theoretical value of 1.0, and one cannot reject the null that $\delta_1=1$ at any reasonable significance level. Of greater interest to us, the estimated coefficients on $(d \times RC)$ are negative for both above and below normal states, and significantly different from zero under three of four specifications, in spite of the imprecision of estimation when we use RC_{ij}^H as an instrumental variable. Indeed, these pastoralists appear to overadjust, in the sense that the statistically significant δ_2 estimates are all less than -1. We reject the null hypothesis of perfect updating at the five percent level. In recognition of possible censored data problems – although the degree of censoring is not extreme – we also estimated the updating equation using Tobit techniques. These results, shown in Table 3, are qualitatively identical to the OLS results.²¹ 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

²⁰ It is unlikely that these variables directly affect the accuracy (relative to the DMC forecast) of an individual's priors.

²¹ 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 heteroscedasticity must be modeled as structural, in this case using a multiplicative form, $\sigma_i = \sigma e^{y'z_i}$, where z_i included ROAD, TLU, EDU, and KENYA. We found the parameter 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.

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.

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 above. Before reporting the results of the indirect estimation approach and to facilitate the interpretation of these results, it is helpful to 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 (10) and (10a)). Table 4 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 4 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 4 indicate that overall the DMC forecast was mostly received as bad news, although 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 5, reinforce the findings of the direct approach and provide an additional insight concerning asymmetric updating. The coefficient estimate on the *furmat* dummy variable, β_{11} , is positive and significant in places that had enjoyed uncommon between-season rains.²² This implied optimism can be explained by positive mood effects as described in Hirshleifer and Shumway (2001) or by a belief in the ‘law of small numbers’ (Tversky and Kahneman 1971) or the ‘hot hand’ (Gilovich, et al. 1985), whereby small sequences are considered representative of their generating process.

Furthermore, 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 β_{12} coefficients on GOOD are uniformly negative and strongly significant in the case of above average rainfall forecasts. Recall that the GOOD variable in the indirect method permits identification of prospective asymmetric updating of beliefs in response to messages that are more or less optimistic than the respondent’s priors. We find consistent evidence against the null of symmetric response and in favor of the alternate hypothesis that pastoralists assimilate relatively good news about the most desirable state of nature more rapidly or completely than relatively bad news or even relatively good news about the least desired state of nature (below normal rainfall). Indeed, at the five percent significance level we cannot reject the joint null ($\beta_{12}=0$, $\beta_{13}=-1$) that optimistic forecasts are accepted as objective probabilities. Climate forecast information seems to have both sign and magnitude effects on respondents’ belief updating processes.

²² 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.

A few other results from Table 5 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 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. forthcoming).

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 between-seasons rains formulate relatively more optimistic (higher) expectations for continued above normal rainfall. These results suggest a tendency toward optimism manifest in updating processes that differ

according to the direction in which one is led to revise prior beliefs. These general findings are robust to a variety of different estimation methods meant to address various econometric complications. In short, pastoralists appear to update their climate expectations asymmetrically, with a cognitive bias towards optimism.

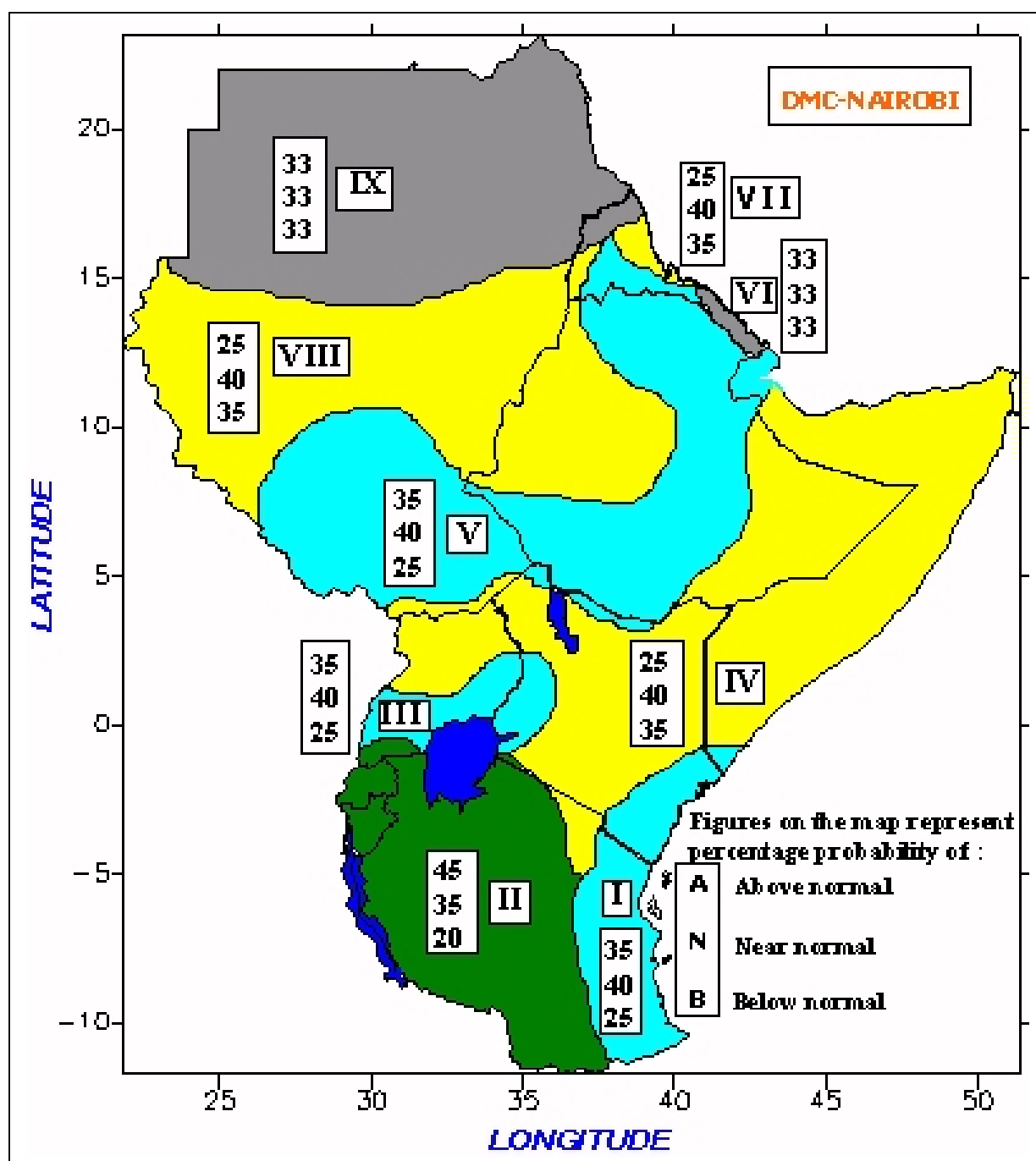


Figure 1 DMC forecast for the 'long rains' season (March-May) 2001

Table 1 Estimated (OLS) coefficients in linear probability model of receipt of and confidence in the DMC forecast (* (**) indicates statistical significance at the 10% (5%) level).

Variable	Coefficient	Std. Error
Intercept	0.385 *	(0.237)
Male {0,1}	0.003	(0.037)
Education (years)	0.037 **	(0.013)
Age	-0.014	(0.009)
Age ²	0.012 *	(0.008)
Cultivation {0,1}	-0.078 **	(0.040)
Livestock (TLU)	0.0006	(0.0007)
Radio {0,1}	0.094	(0.067)
Kenya {0,1}	0.008	(0.038)
Road {0,1}	0.119 **	(0.040)
R ²	0.18	
Breusch-Pagan (d.f.=10)	68.7	

Table 2 Coefficients for the direct (OLS) approach to estimating the updating equation (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	
d_{ij}^s	1.00 **	1.04 **	1.00 **	0.58 **
	(1.59E-17)	(0.032)	(1.52E-17)	(0.118)
$d_{ij}^s \times (RC_{ij})$	-1.89 **		-1.31 **	
	(0.266)		(0.037)	
$d_{ij}^s \times (RC_{ij}^H)$		-0.49		-1.74 **
		(0.396)		(0.408)
Breusch-Pagan (d.f.=1)	108.6	-117.1	763.2	81.8

Table 3 Tobit coefficients for the direct approach to estimating the updating equation (dependent variable, $d_{ij/DMC}^s$, 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)	(0 ; 6%)		(19% ; 0)	
d_{ij}^s	1.04 **	1.10 **	1.00 **	0.83 **
	(0.064)	(0.066)	(0.005)	(0.065)
$d_{ij}^s \times (RC_{ij})$	-1.83 **		-1.27 **	
	(0.073)		(0.005)	
$d_{ij}^s \times (RC_{ij}^H)$		-0.54		-2.67 **
		(0.512)		(0.362)

Table 4 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 5 OLS coefficients for the indirect approach (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	25.5 **	25.3 **	24.7 **	28.0 **
	(10.0)	(13.0)	(7.6)	(9.4)
Male {0,1}	2.93	2.77	-0.81	-0.53
	(2.3)	(2.2)	(1.7)	(1.7)
Age	-0.41	-0.34	-0.24	-0.37
	(0.35)	(0.45)	(0.31)	(0.35)
Age ² ($\div 100$)	0.40	0.37	0.28	0.39
	(0.31)	(0.38)	(0.29)	(0.32)
Cultivation {0,1}	-0.83	-3.78	-1.05	-1.20
	(2.3)	(2.7)	(1.7)	(1.8)
Livestock (TLU)	-0.035	0.029	-0.004	-0.006
	(0.087)	(0.084)	(0.086)	(0.087)
Livestock ² ($\div 100$)	0.023	-0.001	0.018	0.022
	(0.049)	(0.048)	(0.046)	(0.044)
Kenya {0,1}	2.42	0.71	-0.72	0.30
	(2.2)	(2.6)	(1.7)	(1.9)
Furmat {0,1}	10.8 **	9.6 *	2.5	1.7
	(5.0)	(5.4)	(2.7)	(3.1)
RC _{ij}	4.7		-10.2	
	(3.5)		(8.7)	
RC _{ij} ^H		-3.1		-3.9
		(12.2)		(10.9)
GOOD _{ij} ^s	-0.60 **		-0.83 *	
	(0.15)		(0.49)	
GOOD _{ij} ^{Hs}		-1.75 **		-0.10
		(0.38)		(0.42)
Breusch-Pagan (d.f.=10)	92.4	108.1	13.2	13.3

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