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What determines perceived value of seasonal climate forecasts? A theoretical analysis

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ABSTRACT

Seasonal forecasts have potential value as tools for the management of risks due to inter-annual climate variability and iterative adaptation to climate change. Despite their potential, forecasts are not widely used, in part due to poor performance and lack of relevance to specific users' decision problems, and in part due to a variety of economic and behavioural factors. In this paper a theoretical model of perceived forecast value is proposed and applied to a stylized portfolio-type decision problem with wide applicability to actual forecast users, with a view to obtaining a more complete picture of the determinants of perceived value. The effects of user wealth, risk aversion, and perceived forecast trustworthiness, and presentational parameters, such as the position of forecast parameter categories, and the size of probability categories, on perceived value is investigated. Analysis of the model provides several strong qualitative predictions of how perceived forecast value depends on these factors. These predictions may be used to generate empirical hypotheses which offer the chance of evaluating the model's assumptions, and suggest several means of improving understanding of perceived value based on qualitative features of the results.

1. Introduction

It has been widely argued that an ability to cope with current climate variability is a necessary though not sufficient step for adaptation to climate change (Washington et al., 2006; Cooper et al., 2008). Managing risks due to inter-annual climate variability is especially important in developing countries, due to the importance of rain-fed agriculture to their economies, the relative scarcity of risk distribution institutions and coping mechanisms such as insurance and irrigation, and the greater human costs of adverse climatic conditions on their vulnerable populations. Seasonal predictions – forecasts of climatic conditions 3–9 months into the future – are a promising tool for informing ex-ante coping strategies. Farmers who have access to reliable and accurate forecasts can plant drought resistant crops in times of water-stress, and high yield varieties in good years. In general, advance warning of what to expect from the coming growing season provides opportunities for livelihood diversification, and the maximization of returns from productive activities.

As an example of the current operational efficacy of seasonal climate predictions, consider the case of the African continent. Climate change projections for Africa point to plausible, extreme futures with substantial reduction in streamflow (de Wit and Stankiewicz, 2006), possible mobilization of vast dunefields which have been stable since the mid Holocene (Thomas et al., 2005) and attendant undermining of food security (Lobell et al., 2008). Attention is understandably being increasingly focused on how Africa can meet the challenges of coping with a changed climate. At the same time, Africa has served as a forerunner in the degree of formalized organization surrounding seasonal climate prediction. Climate Outlook forums, which aim to generate consensual regional predictions, have been running longer in Africa than anywhere else and have recently celebrated their 10 year anniversary (Patt et al., 2007). Taken together, it might seem that Africa is making good progress towards attaining this first, necessary step towards dealing with climate change. But inspection of the World Climate Research Program's White Paper on Seasonal Prediction (Kirtman and Pirani, 2007) which reviews the status of prediction quality and value, makes for disconcerting reading. While Africa may have the longest running climate outlook forums in the world, there are few examples of the actual uptake of seasonal prediction information on the continent (Tarhule and Lamb, 2003).

Understanding the root causes of the lack of uptake and low perceived value of seasonal prediction information is a vital task, given the overwhelming importance of these timescales of climate information and adaptive responses. A growing literature investigates the determinants of forecast uptake and forecast value (e.g. Stern and Easterling, 1999; Patt and Gwata, 2002; Roncoli, 2006). Several research methodologies, with disciplinary origins in

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meteorology, psychology, anthropology, and economics, have been brought to bear on the problem. Amongst the meteorological community, attention has naturally been on prediction quality, or more specifically improving prediction quality through increasing skill (Palmer and Anderson, 1994), with several promising approaches having been evaluated in Africa (e.g. Shongwe et al., 2008). Psychological approaches (National Research Council, 2006; Nicholls, 1999) emphasize the role of heuristics and biases in explaining human decision making under uncertainty, and shed light on the difficult problem of understanding how decision makers interpret probabilistic forecast information (Gigerenzer et al., 2005; Roulston and Kaplan, 2008), and what can be done to communicate such information effectively (Patt and Dessai, 2005). Anthropologists and human geographers widen the scope of the inquiry from the individual to the cultural and institutional context in which forecasts are produced and received. Emphasis has been placed on the importance of achieving a 'fit' between the intrinsic scientific properties of forecasts, prevailing local environmental conditions, and the needs of, and constraints on, human actors (Orlove and Tosteson, 1998). Others have shown how political, institutional, and cultural contexts can affect users' flexibility to make use of forecasts (Rayner et al., 2005; Koch et al., 2007; Lemos and Dilling, 2007; Ziervogel, 2004).

Given the scientific and human complexity of the forecast valuation problem, what can the idealized models of economic theory contribute to our understanding of the determinants of value and forecast uptake? Quantitative analytical models that link economic decision theory with metrics of forecast performance have been extensively used to derive normative estimates of forecast value (see e.g. Katz and Murphy, 1997; Nelson and Winter, 1964; Adams et al., 1995; Jones et al., 2000). These models yield insights into how decision structure interacts with forecast quality to determine value in the idealized case in which human decision behaviour conforms to the stringent rationality assumptions of standard economic models. They benefit from a powerful analytical framework that is able to produce clean theoretical results. Yet there are few examples of direct empirical tests of the positive predictive power of these models (see Stewart, 1997 for a summary of empirical work that focusses mainly on short-term weather forecasts). Empirical studies (e.g. Luseno et al., 2003; Patt et al., 2005) have thus far found it difficult to make direct value estimates owing largely to the complexity of real-world decision environments, and are thus of limited use for ascertaining the veracity of economic models. Thus these models currently occupy an uneasy space in our theoretical arsenal. While their value as tools for defining normative benchmarks against which reality may be compared is clear, we must as yet remain equivocal on their utility as tools for informing policies designed for real forecast users.

In this paper we explore the predictions of a new model of forecast value based on economic decision theory. Given the argument in the previous paragraph this may seem like a misguided contribution – perhaps if we do not know the epistemic status of extant models adding another to the pot will be of limited value? In the remainder of the paper we argue that the model we offer serves three valuable purposes. First, since it incorporates a diverse set of behavioural, economic, and forecast parameters into a coherent analytical framework it is more likely to be applicable (and thus testable) in real decision contexts than the existing, somewhat too stylized, set of models.[1] Second, it allows the interactions between the determinants of forecast value to be assessed, thereby suggesting explanations of perceived forecast value patterns that are not accessible to frameworks that focus on isolated variables. And third, owing to its increased scope and applicability to diverse decisions, it makes definitive predictions about the dependence of forecast value on economic and forecasting primitives, and thus offers strong hypotheses that can be used to empirically test the usefulness of conventional economic decision theory as a tool for understanding perceived forecast value. The model thus serves both methodological and practical goals.

Section 2 outlines the model and its assumptions. The model is then specialized to a particular stylized decision problem in Section 3, where an idealized crop-choice decision is presented. Section 4 analyses the model in order to discern the influence of wealth, risk aversion, and perceived trustworthiness on perceived forecast value. The final results section, Section 5, explores the effects of alternative forecast presentations (forecasts from ensembles of different sizes, and the effect of the choice of forecast parameter categories) on perceived value. Section 6 discusses the modeling findings and their policy relevance, and concludes.

2. Forecast valuation model

The model we investigate is an extension of standard results in expected utility theory and the economics of information (see e.g. Gollier, 2001; Johnson and Holt, 1997) to the case of probabilistic forecasts from an ensemble of numerical climate models. Probabilistic prediction systems are firmly entrenched in the contemporary approach to seasonal climate information (Hagedorn et al., 2005) but are often cited as a major stumbling block in the uptake of forecasts. A variety of reasons are posed as an explanation for this, including cognitive biases in the understanding of probabilities (Nicholls, 1999), difficulties of reconciling deterministic operational decision making with probabilistic futures, and lack of templates of probabilistic responses, particularly in farming (Hayman et al., 2007). On the other hand, some studies suggest that users respond well to probabilistic information (e.g. Patt et al., 2005). We focus on ensemble probabilistic forecasts as they are the tools of choice for generating seasonal forecasts for most of the large forecasting centres, and are commonly believed to have the most potential for improvements in skill. In addition, the information they provide is ideally suited to many risk management applications, as they provide a full distribution of possible outcomes, and thus allow users to choose strategies that hedge their risks based on the forecast probabilities. The example we develop below is designed with this decision context in mind.

The goal of our modeling work is to quantify the dependencies of perceived forecast value. Perceived value is of necessity a subjective quantity, and, as described in the previous section, is influenced by many behavioural, cultural, and economic factors in addition to objective scientific measures of forecast performance. A model of perceived value which attempts to account for several of these factors was developed in Millner (2008). The model was applied to a simple cost-loss decision problem (Katz and Murphy, 1997), and the effect of perceived accuracy on perceived value was determined. Here we apply the model in the more complex case of a continuous choice between two risky assets (economists refer to such problems as portfolio problems). This decision problem is relevant in many real-world contexts, from the crop choices of farmers and the inventory decisions of small-businesses, to the strategies adopted by natural resource managers and aid workers. We perform a complete analysis of the parameter space of the model for a simple stylized crop-choice problem, and obtain several new results. Our modeling approach takes a very optimistic view of the forecast user's understanding of ensemble probabilistic

[1] While these factors have been addressed individually by several authors (e.g. risk aversion is accounted for in the analysis of Jones et al. (2000), and perceived accuracy in the framework employed by Adams et al. (1995), we are unaware of any framework that accounts for them all at once. In addition, we are not aware of any theoretical frameworks that address the effect of forecast presentation on perceived value.

forecasts, and indeed of her decision making behaviour (users are assumed to be expected utility maximizers). As such, the results we report are perhaps most appropriately interpreted as a best case scenario, providing an upper bound on the perceived value of forecasts. Despite these optimistic assumptions, and the relative parsimony of the model, we will see that it generates interesting hypotheses about the interplay of factors that may contribute to users' appraisals of forecast value.

The model specifies the details of the user's decision problem, how she makes decisions based on available information, how she processes new information, and also her understanding of the details of the ensemble which generates the forecasts upon which she acts. We outline the formal details of the model below.

Users are assumed to be expected utility maximizers. Given a set of possible actions X, and a set of states of the world S, users choose an action $x^* \in X$ which satisfies:

$$x^* = \operatorname{argmax}\left(\sum_{s\in S} p(s)U(c(x,s))\right). \tag{1}$$

In this expression U is the utility function, which we choose to be of the constant relative risk aversion form:

$$U(W) = \begin{cases} \dfrac{W^{1-r}}{1-r} & r \neq 1 \\ \ln W & r = 1 \end{cases}, \tag{2}$$

where the constant r is the coefficient of relative risk aversion. r parameterizes the user's attitude to risk, with values close to zero implying she is close to risk neutral (i.e. she treats uncertain consequences as equivalent to their expected value), while larger values imply a degree of risk aversion (i.e. she treats uncertain consequences as less desirable than their expected value). The consequence function $c(x, s)$ is the consequence of taking action x when the state of the world is s, and thus encodes the details of the decision problem. $p(s)$ is the user's beliefs regarding the probability of state s. Given a probability density forecast $\underline{\pi} = \underline{\pi}(s')$, the user is assumed to update beliefs using Bayes' theorem:

$$p(s|\underline{\pi}) = \frac{\mathcal{P}(\underline{\pi}|s)\, p_c(s)}{q(\underline{\pi})} \tag{3}$$

Here $\mathcal{P}(\underline{\pi}|s)$ is the likelihood of receiving forecast $\underline{\pi}$ in state of the world s, $p_c(s)$ represents the user's beliefs in the absence of forecast information, which for simplicity will be assumed to coincide with the climatological distribution of the forecasted variable, and the normalization factor $q(\underline{\pi})$ is the total probability of receiving forecast $\underline{\pi}$. We now assume two levels of democracy in the user's beliefs about the trustworthiness of forecasts. We assume inter-model democracy, i.e. each member of the forecast ensemble is assumed to be equally trustworthy, and intra-model democracy, i.e. if an ensemble member makes an incorrect forecast, it is believed to be equally likely to be a forecast of any of the incorrect states of the world. Using these assumptions, and denoting the number of ensemble members as N, we can write the likelihood function as a multinomial distribution,

$$\mathcal{P}(\underline{\pi}|s) = N! \prod_{s'\in S} \frac{[L(s'|s)]^{N\underline{\pi}(s')}}{[N\underline{\pi}(s')]!}. \tag{4}$$

where the likelihood matrix $L(s'|s)$, which encodes intra-model democracy, is given by:

$$L(s'|s) = \lambda\delta_{s's} + \frac{1-\lambda}{|S|-1}(1-\delta_{s's}) \quad , \tag{5}$$

where $\delta_{s's} = 1$ if $s' = s$, and zero otherwise. The parameter λ controls how trustworthy the user believes the forecasts to be, with $\lambda = 1$ corresponding to forecasts that are believed to be infallible, and $\lambda = 0$ corresponding to forecasts that are believe to be guaranteed to be incorrect. Finally, the total perceived value V of an ensemble forecast system is defined by:

$$\begin{aligned}\sum_{s\in S} p_c(s)U(c(x^*_{p_c(s)}, s) + V) &= \sum_{\underline{\pi}} q(\underline{\pi})\left(\sum_{t\in S} p(t|\underline{\pi})U(c(x^*_{p(t|\underline{\pi})}, t))\right) \\ &= \sum_{\underline{\pi}}\sum_{t\in S} \mathcal{P}(\underline{\pi}|t)\, p_c(t)U(c(x^*_{p(t|\underline{\pi})}, t)),\end{aligned} \tag{6}$$

where $x^*_{\tilde{p}(s)}$ is the action that maximizes expected utility (1) when beliefs over states of the world are given by $\tilde{p}(s)$. Thus, the perceived value of the forecasting service is defined as the fixed amount we have to increase the consequences of the user's actions by in order to make her indifferent between having only her climatological knowledge and having access to the forecasts as well. Note that on the right hand side of this equation we sum over the expected utility of the user's optimal actions (which differ for each forecast) for every forecast it is possible to receive, weighted by the total probability with which the user believes they will occur.[2] Thus the right hand side represents the total expected utility of the forecasting system, while the left hand side represents the total expected utility the user achieves without forecasting information.

3. Hedging between two risky assets

In order to explore the dependencies of the value function V a particular decision problem must be specified. A stylized hedging decision will be considered, in which a user must decide between two risky assets. Such decisions, in which the decision maker can protect herself against variability by holding a combination of assets with different risk profiles, are regarded as plausible adaptation measures in the face of climate variability (Cooper et al., 2008)and have been investigated in the context of seasonal prediction information, for example in Argentina (Messina et al., 1999; Podesta et al., 2002) and South Africa (Bharwani et al., 2005). The structure of this decision problem is relevant to many real-world scenarios, and also allows the effects of forecast presentation to be meaningfully investigated.

Below we describe a particular example of such a decision in the context of making a choice between two crop varieties which have temperature dependent yield distributions. The example is however generic to any situation in which users are faced with the choice between two options with uncertain outcomes.

Suppose that the forecast user is a farmer faced with a choice between two crop varieties with different responses to average temperature[3] during the growing season. It will be assumed that the crop varieties fetch the same price on the market, so that all the farmer cares about is crop yield. Alternatively, one can view the yield curves as revenue curves, where it is assumed that the relative prices of the two crops are independent of temperature. Thus we neglect the general equilibrium effects of climatic variability for the sake of simplicity.[4] See Arndt and Bacou

[2] For an ensemble of size N, and $|S|$ states of the world, there are $\binom{N+|S|-1}{|S|-1}$ possible density forecasts. Thus the right hand side of the value equation can have a very large number of terms. For example, setting $N = 20$, $|S| = 10$ gives over 10 million possible density forecasts.

[3] We make temperature the independent variable for expositional simplicity. The reader is free to exchange temperatures for growing degree days. We avoid precipitation since it is slightly more difficult to represent statistically, however the results could easily be modified to account for any risks.

[4] Note that there is no difficulty in including these effects in our model in principle. One can simply replace the exogenously specified yield distributions with revenue distributions determined by the equilibrium conditions of a competitive market. However, since many crops in the developing world are produced for export, equilibrium prices are often determined globally, not locally. This makes the problem of determining prices a very difficult one.

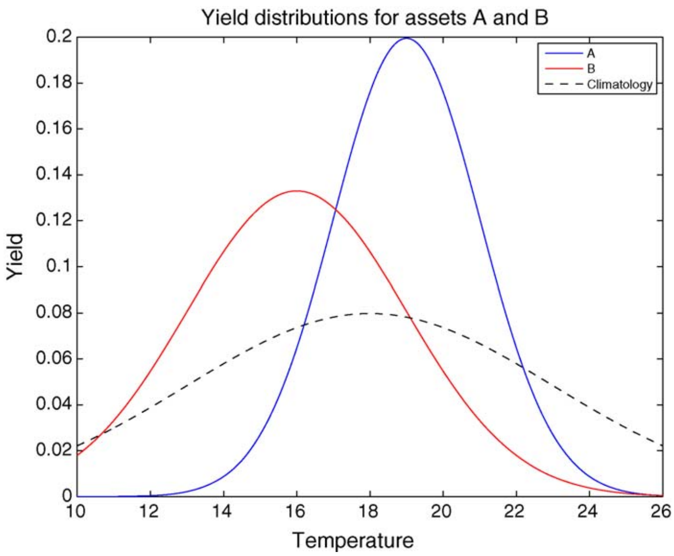

Fig. 1. Yield distributions of crops, $A(\tilde{s})$ and $B(\tilde{s})$, and climatological distribution of average seasonal temperature, $p_c(\tilde{s})$. The yield of crop A is given by the blue curve, crop B the red curve, and the climatology the dashed black curve. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)

(2000) for an analysis of the general equilibrium effects of seasonal prediction and climate variability.

Assume that crop A is a high yield variety which achieves optimal yields when the average temperature is 19 °C. However, it is relatively sensitive to persistent seasonal temperature variations, its yield falling off quickly when average temperature diverges from 19 °C. Crop B generally has lower yields except when the growing season is cool – its optimum average temperature is 16 °C. In addition, it is less sensitive to divergences from its optimal temperature, yielding moderate growth over a wider range of temperatures than crop A. Assume that the climatological distribution for average temperature over the growing season is a normal distribution with mean at 18 °C, and a standard deviation of 5 °C. The yield distributions and climatology are plotted in Fig. 1.

What proportion of her land should the farmer plant with each of the crops? If the farmer were risk neutral (i.e. the coefficient of relative risk aversion $r = 0$), she would plant her entire field with crop A, as her expected returns are greatest for this choice. However, farmers are concerned not only with the magnitude of their earnings, but also their reliability (Rosenzweig and Binswanger, 1993). Most farmers would be willing to sacrifice some of their harvest in order to ensure a steady stream of income. This is due to the damaging effects of income volatility, especially in situations in which storage is expensive or prohibited by the nature of the crop, insurance is unavailable, and in the absence of other sources of income which are uncorrelated with climate (Dercon, 2002). This implies that when faced with the choice between crops A and B, they plant a percentage of their fields with crop B, the low yield variety. The more risk averse they are, the greater the fraction of crop B planted, since this provides the least volatility in their income. Thus planting a mixture of crops provides a measure of insurance against alternative outcomes. This discussion is formalized below.

Let the farmer's expected yields per unit area when the state parameter is s be $A(s)$ and $B(s)$ respectively. In our example, s represents a specified range of average temperatures during the growing season which corresponds to a parameter category of the forecasts. Let the proportion of her field which the farmer plants with crop A be x. Assume that the whole field is cropped, and that the farmer's initial level of wealth is W.[5] The consequence function is thus $c(x, s) = W + xA(s) + (1 - x)B(s)$. Then the farmer's decision problem is,

$$\max_x \sum_{s \in S} p(s)U(W + xA(s) + (1 - x)B(s)), \tag{7}$$

where the farm area and crop price have been normalized to one.[6] For the constant relative risk aversion utility function (2), this implies that x must satisfy:

$$\sum_{s \in S} p(s)\left(\frac{A(s) - B(s)}{(W + xA(s) + (1 - x)B(s))^r}\right) = 0, \tag{8}$$

where r is the coefficient of relative risk aversion. This equation has a unique solution since the utility function is concave in x. Thus given beliefs $p(s)$, the proportion of the field the farmer assigns to each crop can be computed.

Now that the decision problem has been fully specified we are able to solve the model for a variety of parameter values and forecast configurations. The rest of the chapter presents the results of this procedure and interprets them with respect to forecast uptake.

4. Effects of user wealth, risk aversion, and perceived trustworthiness

Much of the attention in the formal forecast valuation literature is focussed on measures of forecast quality as determinants of forecast value (Katz and Murphy, 1997). Considerably less attention has been paid to behavioural and economic constraints on users' ability to extract value from forecasting information (exceptions include Jones et al., 2000; Smith and Roulston, 2004). Yet empirical studies tell us that such factors can play an important role in determining rates of forecast uptake (National Research Council, 2006; Roncoli, 2006). It is thus vital to understand the implications of economic models that include partial representations of these factors, so that they may be compared with the available evidence, and used to design new empirical hypotheses.

The behavioural and economic factors we will focus on in this section are the user's wealth level, attitude to risk, and perception of forecast accuracy. There are few empirical studies that investigate the effects of these factors on forecast usage directly and quantitatively. Phillips (2003) used a survey methodology to investigate the effect of asset wealth on the uptake of seasonal ENSO forecasts in 1997/98 and 1998/99 amongst communal farmers in Zimbabwe. She found that access to forecasts was positively correlated with asset wealth in 1998/99, when media coverage of the La Niña event was low, but that access to forecasts was nearly universal in 1997/98, when media coverage of the El Niño event was wide-spread. In 1997/98, when almost all farmers had access to forecasts, the survey asked which of three strategies – change of planting area, planting date, and crop mix – the farmers engaged in based on forecast information. The frequencies of adoption of each of these strategies were not strongly correlated with asset wealth in this year. In 1998/99 however, a larger proportion of farmers in high asset classes planned to change their cropping area than in low asset classes. While this result suggests a greater responsiveness to forecast information amongst the wealthier farmers, it is not sufficient to resolve the effect of asset wealth on information value. It is necessary to know how much

[5] The units of W, the crop yields A and B, and forecast value V, have not yet been defined. We thus define a baseline unit $u = \int_{-\infty}^{\infty} A(\tilde{s})\, p_c(\tilde{s}) d\tilde{s}$, the expected yield of crop A. This is the average yield that a risk neutral farmer would achieve. Throughout this chapter wealth and value are expressed in units of u.

[6] It is assumed for simplicity that there is no budget constraint—the farmer can plant any proportion of crops, even if the price she must pay for them exceeds W.

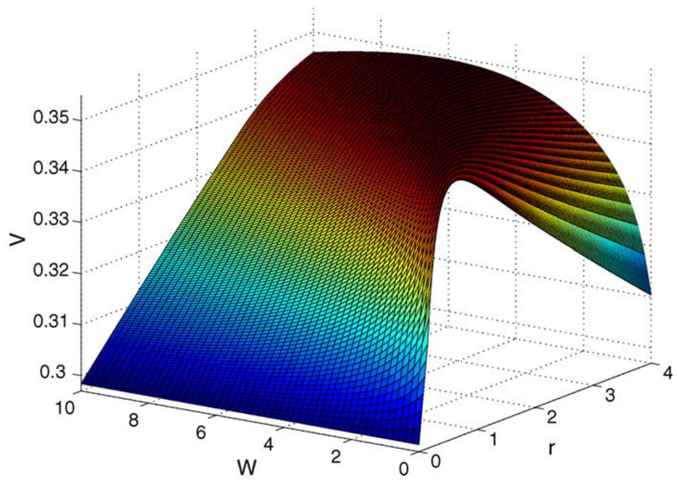

Fig. 2. Perceived forecast value as a function of wealth (W) and risk aversion (r) of the user ($\lambda = 0.9$, $N = 10$, tercile categories).

beliefs and strategies were altered based on the forecast, and not simply whether there was a change, in order to estimate the effect of wealth on forecast value.

A different study of pastoralists in Southern Ethiopia and Northern Kenya (Luseno et al., 2003) found little evidence of behavioural change based on forecast information. Follow-up work (Lybbert et al., 2007) showed that this is not attributable to lack of updating of beliefs in the presence of a forecast. It was found that the extent to which forecast users update their beliefs based on forecast information is state specific, with a statistically significant adjustment of beliefs for forecasts of below-normal rainfall, but not for forecasts of above-normal rainfall. Thus although there is an asymmetry between states, beliefs are responsive to forecasts, although behaviour may not respond commensurably. What then determines how adjusted beliefs manifest in altered actions? Clearly this will depend on attitudes to risk, the structure of the decision problem, and exactly how different updated beliefs are from prior beliefs. The latter effect is mediated by perceptions of forecast accuracy. In what follows we examine the effects of these factors on perceived value in our model.

Consider the portfolio decision problem described above. Suppose initially that forecasts are issued in tercile categories.[7] The yield corresponding to a given category is taken to be the expected yield over that category. That is, suppose that a category is defined by the temperature interval $[a,b]$, then the yield $A([a, b])$ associated with this category for crop A is taken to be

$$A([a,b]) = \frac{\int_a^b A(\tilde{s})\, p_c(\tilde{s}) d\tilde{s}}{p_c([a,b])}, \tag{9}$$

where $p_c([a, b])$, the climatological probability of category $[a,b]$, is just $p_c([a,b]) = \int_a^b p_c(\tilde{s}) d\tilde{s}$. A similar result holds for crop B. The forecast value equation (6) can then be solved numerically for any set of forecast categories, and any set of parameter values. V is plotted in Fig. 2 for a range of values of r and the initial wealth W, for the yield distributions described in Fig. 1.

W and V are given in units of u, the expected yield of a risk neutral farmer. Thus $W = 1$ corresponds roughly to a farmer who has one harvest 'in the bank'. Empirical estimates of the value of r are notoriously inconsistent (estimates range from $r = 0$ to 100, and are based on studies of such diverse activities as financial markets and auctions, insurance contracts, direct choice experiments, and performance on game shows, see e.g. Binswanger, 1980; Holt and Laury, 2002; Meyer, 2006), however the range considered here is roughly plausible (Gollier, 2001).

The figure yields several interesting insights. The first feature to notice is that when $r = 0$, information value is insensitive to wealth. This is clear from the definition (6) – when U is linear ($r = 0$) the user's wealth drops out of the equation. The second notable feature is that information value is not a monotonic function of risk aversion. For each wealth level, there is some value of r at which information value is maximized. Notice also, that the larger W is, the larger r needs to be before information value begins to decline. This may seem like a counterintuitive result – it may seem that more information should be unambiguously more valuable to a more risk averse individual, since it allows her to better manage the risks she faces. The reason for the characteristic inverted-U shaped dependence of information value on risk aversion is as follows: an increase in risk aversion changes the way the risk is valued, and also changes the actions of decision makers. Recall that computing information value requires us to compare the expected utilities of two decision makers – one who has access to the forecasts, the other who does not. In general, a decision maker with access to forecasts will take on more risk than one who does not, since she attempts to capitalize on the additional information in the forecasts. For low values of r, an increase in r affects decision making strongly, giving rise to an increase in information value. However as r increases, the decision maker becomes more and more conservative – eventually honing in on the actions that minimize her exposure to risk. Thus for large r, actions are no longer affected significantly as r increases. However, as r increases, the value of the additional risk that the forecast user holds declines, leading to a decrease in the value of information. The competition between these two effects leads to the qualitative behaviour illustrated in the figure. See Gollier (2001) for further discussion of the effect of risk aversion on information value.

In general, information value exhibits a more sensitive dependence on r for small wealth levels than for large ones. Thus, according to the model, poor agriculturalists should be expected to have widely varying perceptions of forecast value, depending on their degree of risk aversion. The model would require some fairly fine-tuned parameter values $r \approx 1$ in order to predict that information value is high for the poor. Thus the model points to a possible theoretical reason for the empirical fact that many poor farmers do not make use of forecasts – almost all poor decision makers perceive information as having low value. It also defines conditions under which information will be perceived to be most valuable – wealthy users with high risk aversion, and those poor users whose risk aversion falls in the right range, are predicted to value forecasts the most.

These predictions of the model, while presented here for a particular numerical example, are qualitatively preserved for other risk distributions. Thus the model makes some fairly strong, testable predictions which can be used in empirical applications to assess the veracity of the economic foundations of the model. Simulated choice experiments with farmers, which attempt to illicit their degree of risk aversion, and monitor their management decisions, are a natural test-bed.

Next, we consider the effect of perceived accuracy on forecast value. In Fig. 3 we plot perceived value, but this time fix $W = 1u$, and vary r and λ, the perceived accuracy.

The figure suggests that perceived accuracy λ can have a large, nonlinear, effect on perceived value. Notice that the scale of the V axis is larger than that in Fig. 2. Thus perceived value is likely more sensitive to perceived accuracy than it is to the user's wealth level or degree of risk aversion. The qualitative features of the figure are readily understood. Recall that λ parameterizes the user's belief

[7] i.e., the range of temperatures is broken into three distinct categories of equal climatological probability. Each ensemble member makes a deterministic forecast which falls into one of these categories.

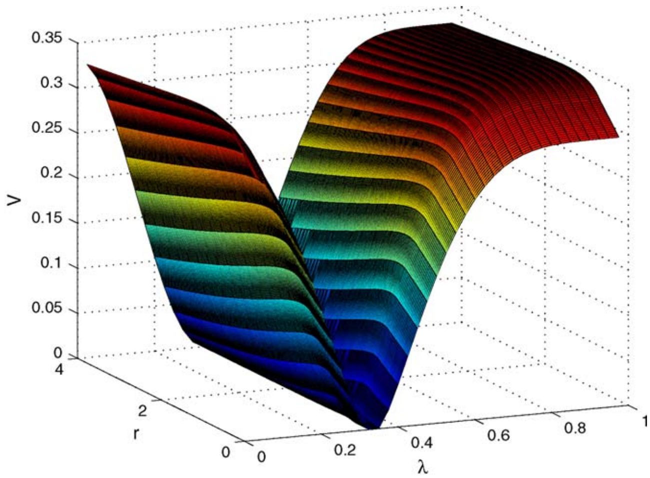

Fig. 3. Perceived forecast value as a function of perceived accuracy (λ) of the forecasts and risk aversion (r) of the user ($W = 1u$, $N = 10$, tercile categories).

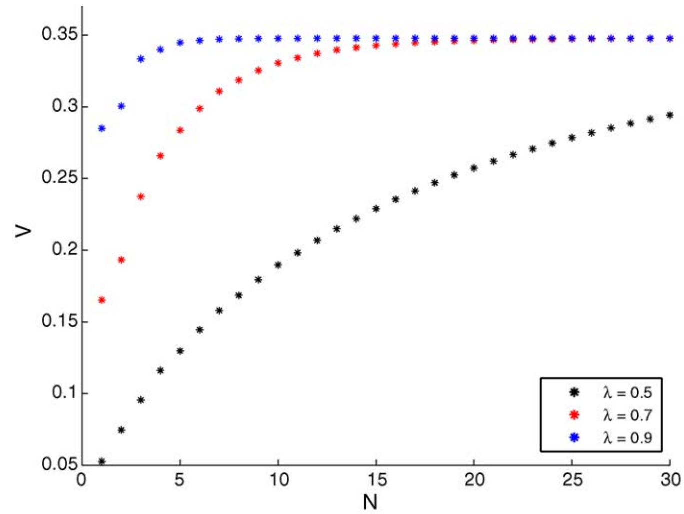

Fig. 4. Effect of ensemble size on perceived value ($W = 1u$, $r = 1$).

that the forecast will be correct, as encoded by her likelihood matrix. When $\lambda = 1/3$, all states of the world are perceived to be equally likely, regardless of which forecast is received, so the user's beliefs coincide with the climatology, and information value is zero. As λ increases above 1/3, the user believes that forecasts are increasingly better than random and so perceived value increases. Perhaps counterintuitively, when λ decreases below 1/3, forecast value also increases. This is due to the user's bayesian updating rule exploiting the negative correlation between forecasts and observations. Put another way, a $\lambda < 1/3$ implies that those states which are *not* forecast by a given model are believed to have probability greater than 1/3, and this information can be exploited by the user, giving rise to positive information value.[8] Real forecasts are calibrated (see e.g. Murphy, 1997) so we would not expect an objective measure of λ less than 1/3. However, subjective beliefs are not similarly constrained. It would be irregular, but not inconceivable, to find users who use forecasts in the hopes of profiting from their consistently poor predictions.

5. Effects of forecast presentation

5.1. Ensemble size

The presentation of seasonal forecasts has routinely settled on probabilities of parameter categories as the prime means of information delivery (e.g. Barnston et al., 2003). Rainfall forecasts from Columbia University's International Research Institute for Climate and Society or the European Centre for Medium Range Weather Forecasts, for example, are typically shown as probabilities in categories of 10% ranging from below-normal through to above normal. Nicholls (1999) has discussed the possible effects of cognitive illusions or user bias in connection with the way probabilities are presented, noting, for example, the possible consequences of anchoring and adjustment, underweighting of base rates, and overconfidence. While we believe these cognitive effects are very important, our model cannot address them explicitly. It can however be used to gain some insight into the relative value of forecasts issued by ensembles of different sizes. If it is assumed that the outputs from an ensemble are not 'dressed' with a parametric distribution (Roulston et al., 2003), then in general large ensembles are capable of issuing forecasts in fine-grained probability categories, while smaller ensembles give rise to coarser stated probabilities. In fact the 'grain' of the probability categories scales like $1/N$, where N is ensemble size.

The analogy between ensemble size and the precision of stated probabilities is not, however, a complete description of the effect of ensemble size on value in our model. The parameter N represents the size of a sample of random variables (the ensemble members). Probability forecasts are represented as histograms of the occupation numbers of the forecast categories for a given sample, and as such, the intervals of probability in which it possible to issue a forecast does indeed scale like $1/N$. However an increase in N is not psychologically identifiable with overconfidence effects due to the precision of stated probabilities. Rather, an increase in N has two effects in our model. First, it reduces the perceived sampling error in forecasts – this leads to sharper, less dispersed, posterior beliefs, as will be demonstrated below.[9] Second, it increases the number of possible forecasts, and makes them more fine-grained, thus allowing for more precise probabilistic judgements. This second effect is more closely related to the overconfidence effect flagged by Nicholls (1999), while the first has been studied independently by Richardson (2001) and Doblas-Reyes et al. (2008), who demonstrate the effect of sample size and simplified probability categories on forecast skill scores. In reality, an increase in ensemble size will have both these effects on forecast value, when we consider the forecasting system as a whole.

A graph of perceived value against ensemble size is plotted in Fig. 4 for our idealized portfolio decision with tercile forecast categories.

In general, perceived value is an increasing function of ensemble size. To understand the qualitative features of this figure, evaluate the expression for the posterior beliefs (3), using

[8] Note that the more forecast categories there are (i.e. larger $|S|$), the more asymmetric the graph of perceived value against λ will be, with perceived value for λ close to zero being lower than perceived value for λ close to one. This is due to our choice of likelihood matrix in (5), which implies that perceived value is zero at $\lambda = 1/|S|$. This can be verified by evaluating the expression (10) at this value of λ to show that updated beliefs coincide with the climatology in this case.

[9] Intuitively, the law of large numbers suggests that for $N \to \infty$, we expect $N\lambda$ of the models to make a correct forecast, and $N(1-\lambda)/(|S|-1)$ models to predict each of the incorrect states, almost surely. Thus the likelihoods $P(\underline{\pi}|s)$ will tend to Dirac delta functions, and their ratios will either diverge or approach zero. This is demonstrated explicitly in (10). For finite N, there is a sampling error that distorts this conclusion – the likelihoods are no longer delta functions, which in turn implies that the users beliefs are more dispersed.

(4) and (5), for a given forecast $\underline{\pi}(s')$ and state s. Some algebra shows that

$$p(s|\underline{\pi}(s')) = \frac{p_c(s)}{p_c(s) + \sum_{t \in S/\{s\}} (\lambda/((1-\lambda)/(|S|-1)))^{N(\underline{\pi}(t)-\underline{\pi}(s))} p_c(t)}, \tag{10}$$

Using this equation, we see that

$$\lim_{N\to\infty} p(s|\underline{\pi}(s')) = \begin{cases} 1 & s = \operatorname{argmax} \underline{\pi}(s') \\ 0 & \text{otherwise.} \end{cases} \quad \text{for} \quad \lambda > (1-\lambda)/(|S|-1), \tag{11}$$

$$\lim_{N\to\infty} p(s|\underline{\pi}(s')) = \begin{cases} 1 & s = \operatorname{argmin} \underline{\pi}(s') \\ 0 & \text{otherwise.} \end{cases} \quad \text{for} \quad \lambda < (1-\lambda)/(|S|-1). \tag{12}$$

Thus for large N the user's beliefs are minimally dispersed, giving rise to high values of information. In general, an increase in N decreases the dispersion of posterior beliefs, hence accounting for the increasing value curves in Fig. 4. This is due to the resolution of sampling error as N increases. The effect of increasingly fine-grained forecasts on value depends on how the user's decision alters with the precision of stated probabilities, and thus depends on the consequence function and the user's utility function. While this cannot be captured analytically in general, Fig. 4 incorporates this effect for our numerical example. Notice, in addition, that forecast value is a concave function of N, suggesting that there are decreasing returns to an increase in ensemble size.

5.2. Which forecast categories?

Many of the freely available forecasts provided by national meteorological organizations are forecasts of standardized categories of the climate variable in question. Forecasts are frequently presented as terciles – users are provided with estimates of the probabilities of above normal, normal, and below-normal conditions, where the categories are determined based on climatological data so that they have equal historical frequency. Many forecast users may however require more specialized information in order to extract value from the forecasts for their particular decision problems. Consider our idealized farmer and her crop-choice problem. She may be a rural small-holder who lacks the necessary funds to purchase proprietary forecasts tailor-made for her decision. Thus she relies on the forecasts broadcast in newspapers and on the radio. Assume for simplicity that these are binary forecasts, a simple 'hot' or 'cold' growing season is forecast with probabilities associated with each category. What effect does the fact that the forecast categories are taken from the climatology, rather than specialized to her decision, have on the value she perceives the forecasts to have? In order to investigate this question the forecast value model is run again, this time for two forecast categories. The position (in temperature space) of the partition between the categories is allowed to vary, and perceived value calculated for each value of the partition position. The climatological partition position is at 18 °C, the mean of the climatological distribution – it is assumed that the national weather service uses this partition. Perceived value is plotted as a function of the position of the partition between the categories in Fig. 5.

The figure suggests that perceived value can be significantly increased by providing forecasts of categories that are tailored to the user's decision problem. Moreover, the less trust the user has in the forecast, the greater the relative effect of tailoring forecast information to her needs. To illustrate this the ratio of perceived value at the optimal partition position to perceived value for a climatological partition position is plotted as a function of λ, the perceived accuracy of the forecasts, in Fig. 6.

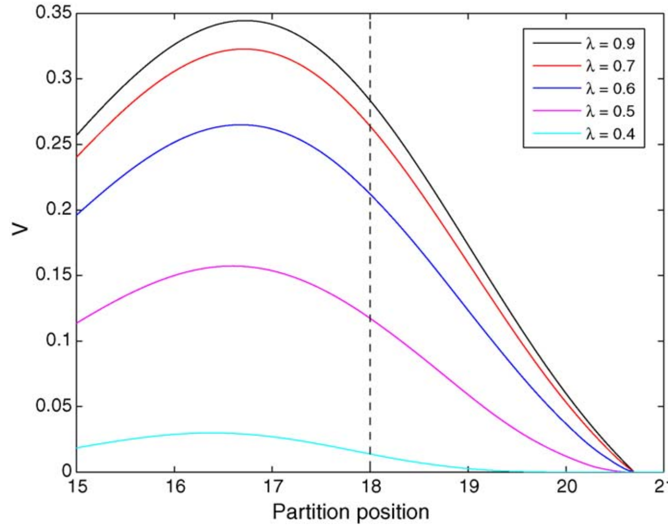

Fig. 5. Effect of the position of the partition between two forecast categories on perceived value ($W = 1u$, $r = 1$, $N = 10$).

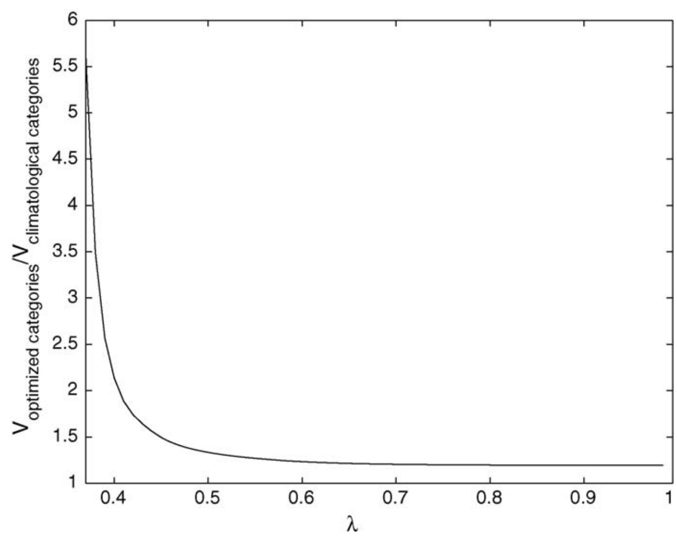

Fig. 6. The less users trust forecasts, the greater the relative effect of the position of the partition between forecast categories on perceived value ($W = 1u$, $r = 1$, $N = 10$).

For strongly trusted forecasts, the ratio approaches 1, and not much is gained by providing tailored forecast categories. However, as trust in the forecast decreases, the (relative) amount to be gained from tailoring forecast categories to user needs increases rapidly.

6. Discussion and conclusions

Although seasonal climate predictions have been available for many years now and although forums for the generation of consensus forecasts have been operational in some regions for more than a decade (Patt et al., 2007), sustained uptake and use of forecasts in decision making is rare. Economic and behavioural constraints on decision making may well form an important part of the explanation for the neglect of such climate information, specifically in developing world agriculture. Using a theoretical model, we inspected the constraints imposed by a variety of economic, behavioural and seasonal prediction related parameters on decision making. The approach forms one end of a spectrum, the counterpart of which is empirical field based investigations. While both are necessary to ensure a fuller understanding of seasonal prediction, the latter are time consuming and resource intensive and necessarily regionally (and probably event) specific. The value of theoretical considerations such as the model considered here, is that they offer hypotheses which can be empirically investigated and therefore have the potential to guide the direction of field studies. While previous models of forecast value based on economic decision theory exist, none has explicitly incorporated the diverse set of determinants that our model allows for. We believe that the increased complexity of the current model allows its predictions to be more immediately applicable in real-world decision contexts, thus allowing for meaningful tests of the legitimacy and usefulness of the standard rationality assumptions upon which it is based. Irrespective of the empirical veracity of the model's predictions, it can still play a useful role as a conceptual guide to understanding how the set of factors it represents interact in determining forecast value. The model shows that these interactions can be quite intricate, and often lead to nonlinear relationships between perceived value and underlying independent variables. It is often difficult to pick apart the relationships between different explanatory variables in understanding field data – we hope that models such as that presented here will contribute to this vital task. It is important to be clear, though, that models are not stand-alone tools for policy generation, and cannot substitute for empirical research. It is with this understanding that the discussion proceeds.

The model has been used to assess the constraints on perceived forecast value imposed by the extent of the resource base (wealth) of farmers and their aversion to risk. It shows that perceived value is non-decreasing in wealth, and non-monotonic in risk aversion. Fig. 2 suggests that for a plausible range of risk aversion parameters the non-monotonicity is most apparent for low wealth values. The consequences of this result for understanding forecast uptake patterns are two fold. First, the model suggests that, *ceteris paribus*, we should expect greater variability in uptake patterns amongst relatively poor forecast users than rich ones. Provided that the distribution of risk aversion within populations at different wealth levels is constant, this result will hold true. There is however some reason to suspect that poor farmers are on average more risk averse than rich ones. Since the model suggests that the range of risk aversion parameters for which poor farmers consider information to be valuable is quite narrow, with a peak at $r \approx 1$ in our example, one might expect poor farmers to have lower subjective valuations than their richer counterparts. Irrespective of wealth effects, the model suggests that risk aversion can have a substantial effect on perceived value.

In order to understand the relevance of these conclusions for informing interventions aimed at improving forecast uptake, consider the interactions between insurance provision and forecast usage. When the price of insurance is actuarially fair,[10] risk averse agents will always prefer complete insurance to holding any risk. Moreover, risk averse agents who have access to fair insurance act as if they are risk neutral. Their production decisions aim to maximize profit as all the risk they face is removed by insurance. What then would the consequences of coupling insurance with prediction systems be? Our model suggests that a reduction in risk aversion is likely to decrease perceived forecast value for all but the poorest farmers. Thus the presence of insurance would be expected to have an adverse effect on forecast uptake. This is not in and of itself a negative outcome – users may well be better off having access to insurance and making little use of forecasts than the converse. Nevertheless, this result may serve to highlight interactions between these two climate risk management tools. The interactions between forecasts and insurance are however complicated by the possibility of skillful forecasts giving rise to inter-temporal adverse selection in the insurance market (Luo et al., 1994; Carriquiry and Osgood, 2008). Thus it is possible that users may utilize forecasts to exploit insurance contracts that are unresponsive to predictable seasonal variability, in addition to using them to inform their production decisions.

The model also shows that perceived accuracy has a strong, nonlinear, effect on perceived forecast value (Fig. 3). Objective forecast skill is only one contributing factor to the user's overall level of trust in the forecasts. Means of increasing the user's trust in objectively useful forecasts other than increasing forecast skill, should be explored. Participatory educational sessions in which users gain familiarity with the products, have been shown to have a positive effect on rates of forecast uptake (Patt et al., 2005), yet are significantly under-funded when compared with efforts to increase forecast skill.[11] Interventions such as these may be more cost effective, and more successful than scientific improvements.

Whereas economic factors relating to wealth, risk aversion, and insurance are all recognizably beyond the remit of the science of seasonal forecasting, the model discussed in this chapter also allows for assessment of parameters well within the control of the World Meteorological Organizations's recognized Global Producing Centres and the Regional Climate Outlook Forums. First we considered the influence of ensemble size on perceived value (Fig. 4). The model suggests that perceived value is an increasing, concave function of ensemble size. Since reported probability categories become more fine-grained as ensemble size increases, marginal improvements in perceived value diminish as probability categories become smaller. There is evidence from the psychology literature (Janiszewski and Uy, 2008) that people tend to anchor their risk assessments to the grain of reported probabilities, implying that fine-grained probabilities may lead to overconfidence in the stated forecasts.[12] An intermediate strategy could successfully offset the negative consequences of this effect without losing much of the informational content of the forecasts.

In addition to the size of probability categories, the choice of forecast parameter categories themselves can have a marked effect on perceived value. We used the model to examine the effect of changing the position of the partition between two parameter categories on perceived value. It was shown (Fig. 5) that tailoring the forecasted parameter categories to the user's decision problem can have a large positive effect on perceived value. Moreover, the less users trust the forecasts, the greater the relative size of this effect (Fig. 6). This suggests that when attempts are made to increase forecast uptake, significant effort should be directed towards understanding the details of users' decision problems. Intimate knowledge of the decision problem could allow forecasters to present information tailored to user needs, thus increasing the chances of forecast uptake. Fig. 6 suggests that this may be especially important for forecasts that are perceived as inaccurate. Such

[10] i.e., the insurance premium is equal to the expectation of the agent's risks.

[11] Patt et al. (2007) say that 'a partnership between the African Union, the United Nations Economic Commission for Africa, the African Development Bank, the United Kingdom Department for International Development, and the Global Climate Observing System, intends to spend up to $200 million over the next 12 years to spread out the use of climate information to help achieve the U.N. Millennium Development Goals.' Compare this to the estimate in Pielke and Carbone (2002) of $5 billion per annum spent on operational and research aspects of weather forecasting in the US alone, and the $2 billion requested budget for the US Climate Change Science Program in 2009 (CCSP, 2008).

[12] This is a danger since it is not clear that outputs from ensembles should be interpreted as probabilities at all (see Smith, 2007). It may thus be good practice to settle on reporting intermediate probability intervals, for example 10% intervals for tercile forecast categories. As such, it is probably best to discourage users from over interpreting numerical probabilities.

forecasts may be accurate enough to carry objective value for decision making, yet users may not make use of them since their perceived value is low. Perceived value may be increased by simply tailoring the forecast categories to the user's needs – the forecasts may still be seen as inaccurate, but no longer irrelevant.

With recent evidence (Kerr, 2008) suggesting that scientific progress on increasing forecast skill has been slow at best, it seems prudent that increased attention should be paid to other factors that may affect the use and value of forecasts where they have been shown to be genuinely skillful. The model presented here suggests that there may be a variety of possibly low cost changes in forecast delivery strategies that could positively affect rates of forecast uptake. In addition, it suggests that linkages between forecasting products and other developmental interventions, such as insurance, need to be more fully explored, since there may be opportunities for mutual reinforcement between them. In general however, detailed knowledge of the particularities of the intended users' economic circumstances and decision problem are necessary prerequisites for understanding the impediments to forecast adoption, and designing interventions that will ultimately increase users' welfare. Hopefully careful field investigations, when combined with theoretical insights from empirically validated models with sound behavioural foundations, can provide these details, and lead to genuine gains for users.

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