Farmer Interest in and Uses of Climate Forecasts for Florida and the Carolinas: Conditional Perspectives of Extension Personnel

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ABSTRACT

In baseline surveys that were conducted in Florida, North Carolina, and South Carolina, extension personnel were asked whether, how, and which farmers would use climate forecasts to manage production and other aspects of their agribusinesses. In making such assessments extensionists use their expertise to account for, the authors assume, net benefits to farmers of the forecasts, given any help that they also expect to provide their clients. Models of conditional probabilities are estimated to show how the assessments depend on the expertise and other characteristics of the extensionist and her clientele. For example, if a person has worked at least 7 years in extension, she is more likely to agree or strongly agree that farmers are interested in using climate forecasts. An extensionist who works with field crop producers is more likely than one who does not to think that a farmer can use climate forecasts to improve planting schedules, harvest planning, crop selection, nutrient management, and land allocation. An extensionist is more likely to assess that farmers who produce particular crops can use climate forecasts to be more successful if she works with them. An extensionist whose clientele's average farm size exceeds 200 acres is more likely to indicate that a farmer can use climate forecasts to improve irrigation management, harvest planning, and crop selection. In addition to serving as references for future work, these conditional assessments almost always provide more nuanced and useful information than unconditional ones about potential farmer interest in and uses of climate forecasts for the three-state region.

1. Introduction

The El Niño–Southern Oscillation (ENSO) and its associated phases—El Niño, Neutral, and La Niña—represents a major interannual climatic variation in the southeastern United States (e.g., Fraisse et al. 2006; Jones et al. 2000) and elsewhere (e.g., Letson et al. 2001). ENSO and other types of climate variability can create production and revenue fluctuations for farmers in the Southeast (e.g., Nadolnyak et al. 2008). Indeed, the economic impacts on farmers of ENSO (e.g., Hansen et al. 1998), drought (e.g., Crane et al. 2010), freeze events (e.g., NOAA-USDA 2008), and other aspects of climate variability in the Southeast can be substantial.

Farmers have access to information, technologies, institutions, and social networks to respond to climate variability (e.g., Lubell et al. 2014; Olmstead and Rhode 2011; Crane et al. 2010). They can use climate information to reduce risks or improve profitability in the southeastern United States (e.g., Adams et al. 1995) and elsewhere (e.g., Meza et al. 2008). As educators and advisors, extension personnel can provide climate information to farmers (e.g., Mase and Prokopy 2014). Their willingness to do so depends on characteristics of themselves, their

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employers or state, and their clientele (e.g., Haigh et al. 2015; Lemos et al. 2014; Breuer et al. 2011).

As agricultural experts, extension personnel can also assess farmer interest in and uses of climate information. The assessments of which we are aware, except for the one in Prokopy et al. (2013), pertain to the southeastern United States. For example, the proportions of extension personnel who agreed or strongly agreed that agricultural producers in their region or county were interested in using climate forecasts were 86.5% at the University of Florida in 2004 (Cabrera et al. 2006) and 67.2% in 2009,[1] 65.1% at North Carolina State University in 2009 (Breuer et al. 2011), and 71.4% at Clemson University in 2011 (Templeton et al. 2014).

Their assessments can matter. Surveying relatively few, easily identified extensionists—agents, specialists, or associates—about possible farmer interest in and use of climate information probably costs less time and money than surveying relatively many or harder-to-identify farmers. Feedback from extensionists has been useful during participatory development, or coproduction, of decision support tools that utilize such information (e.g., Breuer et al. 2008; Cash et al. 2006). Extension agents are highly trusted (e.g., Prokopy et al. 2015) or very important (e.g., Samy et al. 2003) sources of information and are frequently contacted by farmers (e.g., Lubell et al. 2014; Frisvold and Deva 2012). Moreover, the more likely that extensionists assess that farmers want to and can use climate forecasts to improve managerial activities, the more likely they will incorporate the forecasts into their outreach. However, differences in their expertise, values, employers or states, and clientele might affect their assessments, just as these differences affect their willingness to provide climate information. Thus, assessments conditional on characteristics of extensionists and their clients might be more informative than unconditional assessments for determination of the potential adoption by farmers of climate information.

Our research objectives are to analyze the extent to which an extensionist's assessments of whether, how, and which farmers in the Carolinas and Florida would use climate forecasts vary with characteristics of the extensionist and her clientele. Ordered logit and logit models of conditional probabilities (e.g., Train 2009) are estimated for our analyses. Most, but not all, of the state-specific data that we merge to estimate the models were previously described in separate studies about Florida (Cabrera et al. 2006), North Carolina (Breuer et al. 2011), and South Carolina (Templeton et al. 2014). The three studies, however, were focused on extensionists as potential users of seasonal climate forecasts and their roles as educators and advisors of farmers. The study of Prokopy et al. (2013) was similarly focused on agricultural advisors as potential users of historical weather and climate information. Moreover, the sample proportions in the studies from Florida (Cabrera et al. 2006), North Carolina (Breuer et al. 2011), and the upper Midwest (Prokopy et al. 2013) were not used to statistically test whether majorities of extensionists in each state or region had identical assessments. Sample proportions in this paper are initially used for such tests and then subsequently used as dependent variables in econometric models of conditional probabilities. Assessments of extensionists about farmer interest in and uses of seasonal climate forecasts have not, as far as we know, been analyzed with such models.

2. Data sources and variables

The data for our models were merged from individual responses of extensionists to identical or almost identical questions and statements in three baseline surveys. (See Table A1 for the exact phrasing of the relevant questions and statements.) The extensionists in the survey populations worked in agricultural and natural resource management. The original survey was conducted in November and December 2004 among extension agents at University of Florida (Cabrera et al. 2006); 89 of the 166 agents responded. A second survey was conducted in March and April 2009 among extension agents at North Carolina State University (Breuer et al. 2011); 109 of approximately 235 agents responded. The third survey was conducted in January and February 2011 among extensionists at Clemson University (Templeton et al. 2014); 49 of the 171 extension agents, associates, and specialists responded. However, only 199 to 202 of the 247 respondents provided sufficient information for the dependent and independent variables in our models. Thus, the rate of usable responses from the population of 572 extensionists was approximately 35%. The column titled "All baseline" in Tables 1 and 2 has proportions calculated with the data merged from all three baseline surveys.

A follow-up survey identical to the baseline one was conducted among 119 extension agents at the University of Florida in 2009 (Breuer et al. 2010). The response rate was approximately 50%. Some of the follow-up data from the 2009 survey in Florida and the baseline

[1] This proportion was calculated with unreported data from the survey of Breuer et al. (2010).

TABLE 1. Characteristics of extensionists and their clientele with baseline data from the Carolinas and either 2004 (all baseline) or 2009 (FollowUpF09) data from Florida.

Description of independent variable	All baseline	FollowUpF09
FLORIDA (= 1 if respondent works in Florida)	60/202 = 0.297	63/205 = 0.307
NCAROLINA (= 1 if respondent works in North Carolina)	101/202 = 0.500	101/205 = 0.493
SCAROLINA (= 1 if respondent works in South Carolina)	41/202 = 0.203	41/205 = 0.200
NONAGENTSC (= 1 if respondent from South Carolina is an extension associate or specialist)	19/202 = 0.094	19/205 = 0.093
MALE (= 1 if respondent is male)	162/202 = 0.802	150/204 = 0.735
OVER6YREXP (= 1 if respondent has more than 6 years, or at least 7 years, of experience in extension)	148/202 = 0.733	133/199 = 0.668
OWNCOMFARM (= 1 if respondent manages more than 2 acres, or 0.809 ha, of land for agricultural production)	80/202 = 0.396	Not calculable
BIGCLIENTFARM (= 1 if the average farm size of respondent's clientele exceeds 200 acres, or 80.9 ha)	73/202 = 0.361	68/189 = 0.360
FIELDCROP (= 1 if field crop production is relevant to the respondent's work)	89/202 = 0.441	89/205 = 0.434
VEGETABLE (= 1 if vegetable production is relevant to the respondent's work)	82/202 = 0.406	85/205 = 0.415
CATTLEFORAGE (= 1 if beef cattle, dairy cattle, or forage production is relevant to the respondent's work)	80/202 = 0.396	Not calculable
NURSERYGH (= 1 if greenhouse or nursery production is relevant to the respondent's work)	75/202 = 0.371	74/205 = 0.361
PERENFRUITNUT (= 1 if perennial fruit or nut production is relevant to the respondent's work)	70/202 = 0.347	63/205 = 0.307

data from the Carolinas are merged to recalculate sample proportions, which are reported in Tables 1 and 2 under column FollowUpF09. The recalculated sample proportions are compared to sample proportions calculated entirely with baseline data and used to check whether our conclusions about majorities are sensitive to any change that occurred among agents in Florida. However, the data from the follow-up survey in Florida cannot be used to estimate parameters of our models because they lack identifying codes to link individual assessments with characteristics.

Of the respondents, 70.3% worked in North Carolina for North Carolina State University in 2009 or South Carolina for Clemson in 2011 (Table 1). The remainder worked in Florida for the University of Florida in 2004 (Table 1). Thus, FLORIDA, NCAROLINA, and SCAROLINA indicate separate states, universities, and years. Whether the respondent was a nonagent, was male, or had more than 6 years of experience in extension are three other characteristics (Table 1). Sixty percent of respondents managed a farm that was smaller than two acres or were not farmers.[2] The mean size of farms in the Carolinas and Florida was 179 acres in 2007 and 186 acres in 2012 (NASS 2014). Thus, at least one-third of respondents had clients who operated above-average-sized farms (Table 1). The surveys lacked questions about the mean age and education of an extensionist's clients or the proportion of them who were female or nonwhite.

Production of field crops, vegetables, cattle or forage,[3] greenhouse or nursery plants, and perennial fruits or nuts were the first, second, third, fourth, and fifth types of agricultural goods most likely to be relevant to a respondent's work (Table 1). Production of none of the top five selected types of agricultural goods was relevant to 11.7% of the respondents to the three baseline surveys. In this case, production of timber or Christmas trees, turfgrass/landscape, water quality, or an "other" good or service was relevant to their work.[4]

Categorical responses to two statements and a question in the surveys were the sources of data for dependent variables that are analyzed with the estimated ordered logit and logit models (Table 2 and Table A1). The first statement was that growers and producers (including forest owners, livestock producers, etc.) in my region or county are interested in using climate forecasts. Respondents selected one of five options from strongly disagree to strongly agree.

[2] If a respondent from Florida or North Carolina did not answer how much land she managed but consistently answered other questions, the respondent was coded as not a farmer.

[3] Forages grown in pastures or harvested for fodder are produced primarily for cattle. The relevance to an extensionist's work of forage production was highly correlated with the relevance to her work of beef or dairy cattle production. For these reasons and model parsimony, the three activities were combined to create one variable: CATTLEFORAGE.

[4] Production of strawberries or other annual fruit was relevant to the work of 23.8% of the baseline respondents. However, if annual fruit production was relevant, then production of perennial fruit and nuts, vegetables, or greenhouse nursery crops was also relevant. Moreover, working with annual fruit producers did not affect any assessment in preliminary models.

TABLE 2. Assessments of extensionists: dependent variables, sample proportions with baseline data from the Carolinas and either 2004 or 2009 data from Florida, and one-sided p values. FollowUpF09 comprises baseline data from the Carolinas and follow-up data from Florida.

Name and definition of dependent variable	All baseline (p value)	FollowUpF09 (p value)
Farmer interest (= 1 if the respondent strongly agrees or agrees that farmers are interested in using climate forecasts)	144/202 = 0.713 (<0.0001)	128/203 = 0.631 (0.000 122)
Planting schedules (= 1 if clientele could use climate forecasts to improve planting schedules)	158/199 = 0.794 (<0.0001)	151/192 = 0.786 (<0.0001)
Irrigation management (= 1 if clientele could use climate forecasts to improve irrigation management)	133/199 = 0.668 (<0.0001)	132/192 = 0.688 (<0.0001)
Harvest planning (= 1 if clientele could use climate forecasts to improve harvest planning)	130/199 = 0.653 (<0.0001)	120/192 = 0.625 (0.000 328)
Variety or crop selection (= 1 if clientele could use climate forecasts to improve variety or crop selection)	121/199 = 0.608 (0.00141)	118/192 = 0.615 (0.000 919)
Nutrient management (= 1 if clientele could use climate forecasts to improve nutrient management)	120/199 = 0.603 (0.002 23)	109/192 = 0.568 (0.0355)
Land allocation (= 1 if clientele could use climate forecasts to improve land allocation)	108/199 = 0.543 (0.128)	107/192 = 0.557 (0.0647)
Vegetable farmers (= 1 vegetable farmers are likely to be more successful using climate forecasts)	168/200 = 0.840 (<0.0001)	159/194 = 0.820 (<0.0001)
Row crop farmers (= 1 if row crop farmers are likely to be more successful using climate forecasts)	152/200 = 0.760 (<0.0001)	155/194 = 0.799 (<0.0001)
Orchard growers (= 1 if orchard growers are likely to be more successful using climate forecasts)	127/200 = 0.635 (<0.0001)	118/194 = 0.608 (0.001 57)
Nursery operators (= 1 if nursery operators are likely to be more successful using climate forecasts)	121/200 = 0.605 (0.001 82)	106/194 = 0.546 (0.111)
Livestock producers (= 1 livestock producers are likely to be more successful using climate forecasts)	118/200 = 0.590 (0.006 57)	114/194 = 0.588 (0.008 80)

The second statement was, "People I work with can use climate forecasts to improve…" Respondents selected all managerial activities on a list of 11 or 12 types that applied. Nonselection of an activity indicated that a respondent knew her clients could not use forecasts to improve the nonselected activity or did not know if her clients could. The one question was, "Who is likely to be able to use climate forecasts to be more successful?" Respondents checked all managers, jobs, or industries on a list of 13 types that applied. Nonselection of a type of manager indicated that a respondent had a negative or indeterminate assessment.

3. Conceptual framework, formal models, and formal definitions of dependent variables

Our econometric models of the responses to the two statements and one question originate with a conceptual framework of how extensionists make assessments. Extensionists care about their job-related well-being and thus have expertise about farmers and farm management. In their assessments, extensionists account for, we assume, benefits and costs to farmers of using climate forecasts in light of any benefit-increasing or cost-decreasing help that farmers request from them to utilize the forecasts. Although extensionists have expectations about whether the net benefits to farmers would be positive, they do not know the exact monetary values of them. A climate forecast is beneficial to a farmer if he can reduce risk, improve yield, or decrease production cost through decisions that depend on the forecast (e.g., Haigh et al. 2015; Prokopy et al. 2013; Just et al. 2002). A farmer incurs costs—such as time, mental effort, and possibly training—to acquire, process, and apply information (e.g., Just et al. 2002), such as a forecast. Benefits and costs of a forecast depend on, among numerous factors, the type of managerial decision a farmer makes (e.g., Artikov et al. 2006; Mjelde et al. 1988), type of crop(s) for which the decision is made (e.g., Just et al. 2002), size of his operation (e.g., Breuer et al. 2008), and inherent productivity of his state or farm's locale (e.g., Solís and Letson 2013; Meza et al. 2008). The requested help that extensionists expect to provide depends on their willingness to do so and, in turn, on their age-dependent values, crop-specific knowledge, employer's norms for extension, and clientele's farm sizes (e.g., Haigh et al. 2015; Lemos et al. 2014). Thus, an assessment should depend on characteristics of the extensionist, her employer or state, and her clientele.

To formalize our conceptual framework in light of the data, we adapt models of multiple-ordered and binomial choices (e.g., Train 2009). We assume that extensionists know their own utilities and their perceptions of utility differences of farmers. In particular, let U_r^i be respondent r's degree of agreement or disagreement, measured as utility, with the statement that farmers are interested (i) to use climate forecasts. Also, let c_3 be the cutoff level of utility such that $U_r^i > c_3$ signifies strong agreement, c_2 be the cutoff utility such that $c_3 \geq U_r^i > c_2$ signifies agreement, c_1 be the cutoff utility such that $c_2 \geq U_r^i > c_1$ signifies neither agreement nor disagreement, and $c_1 \geq U_r^i$ signifies disagreement or strong disagreement. Now, let $Y1_r = 1$ if $c_1 \geq U_r^i$, and thus respondent r selects disagree or strongly disagree or 0 if not. Let $Y2_r = 1$ if $c_2 \geq U_r^i > c_1$, and thus she selects neither agree nor disagree or 0 if not. Let $Y3_r = 1$ if $c_3 \geq U_r^i > c_2$, and thus she selects agree or 0 if not. Let $Y4_r = 1$ if $U_r^i > c_3$, and thus she selects strongly agree or 0 if not. Let the number of respondents who select agree or strongly agree be $Y \equiv \sum(Y4_r + Y3_r)$.

Let UF_r^a be respondent r's perception of the difference in utility (U) of farmers (F) who are clients and manage activity a with and without climate forecasts. If $UF_r^a > 0$, then respondent r perceives that the incremental utility, or extra net benefit, to her clients of using climate forecasts to manage activity a is positive, and thus the farmers can use climate forecasts to improve activity a. Let $I_{a,r} = 1$ if $UF_r^a > 0$, and thus respondent r checks managerial activity a and 0 if not. Also, let $I_a \equiv \sum I_{a,r}$ be the number of respondents who select activity a on the list.

Similarly, let UF_r^m be respondent r's perception of the difference in utility of type-m farm manager's use and nonuse of climate forecasts for his agricultural production. A type-m manager could be, for example, a row crop farmer. If $UF_r^m > 0$, then respondent r perceives that the incremental utility, or extra net benefit, to a type-m manager of using climate forecasts is positive, and thus the type-m manager is likely to be able to use climate forecasts to be more successful. Let $S_{m,r} = 1$ if $UF_r^m > 0$, and thus respondent r selects the manager of type m and 0 if not. Also, $S_m \equiv \sum S_{m,r}$ is the number of respondents who select a type-m manager on the list.

4. Unconditional probabilities

The variables Y, I_a, and S_m have binomial distributions. Let P_Y, P_{I_a}, and P_{S_m} be the respective probabilities that an extensionist at least agrees farmers in her area are interested in using climate forecasts, thinks her clients could use a climate forecast to improve activity a, and thinks farmers who produce commodities of type m could use climate forecasts for more success. The probability that, under $H_0\colon P_Y \leq 0.5$, at least y of R respondents would at least agree that farmers are interested in using climate forecasts is $\Pr(Y \geq y) = \sum_{j=y}^{R} \binom{R}{j} 0.5^R$. If this probability is less than 0.05, we conclude that a majority of extensionists agree or strongly agree. Alternative hypotheses that P_{I_a} and P_{S_m} exceed 0.50 are tested with analogously calculated probabilities.

5. Econometric models of conditional probabilities

Results of tests about unconditional probabilities might not, however, be as informative or useful as results of tests about the isolated effects that particular characteristics of extension personnel or their clients have on conditional probabilities. To estimate and test such isolated effects, econometric models of conditional probabilities are constructed. To do so, we assume that we cannot completely determine and capture in models what extensionists know about their own utilities and their perceptions of the utility differences of farmers.

Let $U_r^i = \mathbf{X}_r\boldsymbol{\beta} + \varepsilon_{Y_r}$. The 1×15 vector $\mathbf{X}_r$ consists of 12 characteristics of respondent r and her clientele and three number ones. The 15×1 vector $\boldsymbol{\beta}$ consists of 12 parametric effects of the characteristics on utility and three constants c_1, c_2, and c_3, called cut points. The term $\mathbf{X}_r\boldsymbol{\beta}$ is the knowable, nonrandom portion of respondent r's degree of agreement and associated utility with the statement that farmers are interested in using climate forecasts. The term ε_{Y_r} is the unknowable, random portion of utility and has, by assumption, an independent and identical logistic distribution. Thus, as derived in the appendix, the ordered logit probability that respondent r, respectively, 1) strongly disagrees or disagrees, 2) neither disagrees nor agrees, 3) agrees, or 4) strongly agrees with the statement about farmers being interested in using climate forecasts is

$$P_{Y1_r} \equiv \Pr(Y1_r = 1) = \frac{\exp(c_1 - \mathbf{X}_r\boldsymbol{\beta})}{1 + \exp(c_1 - \mathbf{X}_r\boldsymbol{\beta})},$$

$$P_{Y2_r} \equiv \Pr(Y2_r = 1) = \frac{\exp(c_2 - \mathbf{X}_r\boldsymbol{\beta})}{1 + \exp(c_2 - \mathbf{X}_r\boldsymbol{\beta})} - \frac{\exp(c_1 - \mathbf{X}_r\boldsymbol{\beta})}{1 + \exp(c_1 - \mathbf{X}_r\boldsymbol{\beta})},$$

$$P_{Y3_r} \equiv \Pr(Y3_r = 1) = \frac{\exp(c_3 - \mathbf{X}_r\boldsymbol{\beta})}{1 + \exp(c_3 - \mathbf{X}_r\boldsymbol{\beta})} - \frac{\exp(c_2 - \mathbf{X}_r\boldsymbol{\beta})}{1 + \exp(c_2 - \mathbf{X}_r\boldsymbol{\beta})}, \quad \text{or}$$

$$P_{Y4_r} \equiv \Pr(Y4_r = 1) = \frac{1}{1 + \exp(c_3 - \mathbf{X}_r\boldsymbol{\beta})}.$$

Let $UF_r^a = \mathbf{Z}_r\boldsymbol{\lambda}_a + \varepsilon_{I_{a,r}}$ and $UF_r^m = \mathbf{Z}_r\boldsymbol{\lambda}_m + \varepsilon_{S_{m,r}}$. The 1×13 vector $\mathbf{Z}_r$ consists of the number 1 and 12 explanatory characteristics of an extensionist or her clientele. The 13×1 vectors $\boldsymbol{\lambda}_a$ and $\boldsymbol{\lambda}_m$ consist of constants c_a and c_m and respective parametric effects of the 12 characteristics on an extensionist's assessment about how and which farmers in the three-state region would use climate forecasts. The term $\mathbf{Z}_r\boldsymbol{\lambda}_a$ is the knowable, nonrandom portion of respondent r's perception of the incremental utility of a farmer who would use climate forecasts to improve managerial activity a; $\mathbf{Z}_r\boldsymbol{\lambda}_m$ is the knowable, nonrandom portion of respondent r's perception of the incremental utility of a type-m farm manager who could use climate forecasts to be more successful. Error terms $\varepsilon_{I_{a,r}}$ and $\varepsilon_{S_{m,r}}$ represent unknowable, random portions of respondent r's perceptions and have, by assumption, independent and identical logistic distributions. Given our assumptions, the probability that respondent r indicates that the people with whom she works could use climate forecasts to improve managerial activity a is $P(I_{a,r}=1)=[\exp(\mathbf{Z}_r\boldsymbol{\lambda}_a)]/[1+\exp(\mathbf{Z}_r\boldsymbol{\lambda}_a)]$. Also, the probability that respondent r indicates that a type-m manager is likely to be able to use climate forecasts to be more successful is $P(S_{m,r}=1)=[\exp(\mathbf{Z}_r\boldsymbol{\lambda}_m)]/[1+\exp(\mathbf{Z}_r\boldsymbol{\lambda}_m)]$. (See the appendix for derivations.)

Let the unconstrained likelihood functions be L_Y for the extent to which extensionists agree about whether farmers are interested in using climate forecasts, L_{I_a} for their assessments about whether their clients would use climate forecasts to improve managerial activity a, and L_{S_m} for their assessments about whether a type-m manager is likely to be able to use climate forecasts to be more successful. Vectors $\boldsymbol{\beta}$, $\boldsymbol{\lambda}_a$, and $\boldsymbol{\lambda}_m$ are estimated in STATA (StataCorp 2011) with the OLOGIT procedure to maximize L_Y and the LOGIT procedure to maximize L_{I_a} and L_{S_m}. Cut points c_1, c_2, and c_3 and constants c_a or c_m are also reestimated to maximize respective constrained likelihood functions when all other parameters are set equal to zero. The constrained likelihood functions represent models of population proportions. Also, the predicted probability that is calculated with the maximum likelihood estimates of the cut points in the constrained ordered logit model or the constant in each of the constrained logit models equals the proportion of respective responses in the sample (e.g., Train 2009).

An intuitively interpretable measure of the goodness of fit of an unconstrained model of conditional probability for dichotomous- and polychotomous-dependent variables is the scaled R^2 (Estrella 1998). The farther is the scaled R^2 from zero, the better is the fit of the unconstrained model to the data and the less the unconstrained model resembles the constrained model of unconditional probabilities. Moreover, chi-square statistics that are based on differences in the natural logarithms of constrained and unconstrained maximum likelihoods are calculated to test whether the unconstrained models of conditional probabilities fit the data discernibly better than constrained models of unconditional probabilities do. Unconstrained models are used to estimate mean effects of conditioning variables, that is, characteristics of an extensionist or her clientele, on the chances that an extensionist makes affirmative assessments. (See the appendix for details.)

6. Results

a. Are farmers interested in using climate forecasts?

One hundred forty-four of the 202 respondents to the three baseline surveys and 128 of the 203 respondents to the two Carolina surveys and one follow-up survey in Florida agreed or strongly agreed that farmers are interested in using climate forecasts (Table 2). Under the null hypothesis that no more than half of all extension personnel in the three-state region think this way, the probability of observing at least this many affirmative responses is extremely small (Table 2). Thus, regardless of the merged data, a majority of extension personnel in the Carolinas and Florida agree or strongly agree that farmers are interested in using climate forecasts.

Parameter estimates, standard errors, z statistics, and p values for variables in the ordered logit model of probabilities are presented in Table 3. The scaled R^2 is 0.365; the conditional model accounts for almost 37% of the information about the degree to which an extensionist agrees that farmers are interested. The p value for the chi-squared statistic of 83.55 with 12 degrees of freedom for the test of nonzero effects of the characteristics of an extensionist and her clientele is less than 0.0001. Thus, the ordered logit model that depends on those characteristics fits the data better than the constrained, or unconditional, model of ordered probabilities.

The states where extensionists work, having at least 7 years of experience in extension, three types of crop production that are relevant to their work, and not being an extension agent in South Carolina are the variables that statistically affect assessments of farmer interest in using climate forecasts (Table 3). The mean effects on the probabilities that an extensionist agrees or strongly agrees that farmers are interested in using the forecasts range from an increase of 11.0 percentage points if the extensionist has more than 6 years of on-the-job experience to a decrease of 10.4 percentage points if cattle or forage production is relevant to her work (Table 4).

b. Which management activities could farmers use climate forecasts to improve?

Planting schedules, irrigation management, harvest planning, variety or crop selection, nutrient management, and land allocation were the six most selected activities (Table 2). The order of selection frequency remains the

TABLE 3. Ordered logit model ($n = 202$) of the probabilities of the extent to which an extensionist agrees that growers and producers are interested in using climate forecasts.

Variable	Parameter estimate	Standard error	z statistic	Two-sided p value
NCAROLINA	−2.920	0.411	−7.10	0.000
SCAROLINA	−1.447	0.526	−2.75	0.006
NONAGENTSC	−1.364	0.650	−2.10	0.036
MALE	0.192	0.367	0.502	0.601
BIGCLIENTFARM	0.347	0.330	1.05	0.218
OWNCOMFARM	0.377	0.306	1.23	0.218
OVER6YREXP	0.660	0.329	2.01	0.045
FIELDCROP	0.609	0.339	1.80	0.072
VEGETABLE	−0.600	0.356	−1.69	0.092
CATTLEFORAGE	−0.644	0.320	−2.01	0.044
NURSERYGH	0.422	0.332	1.27	0.203
PERENFRUITNUT	0.247	0.363	0.068	0.496
Cutoff 1 (c_1)	−4.668	0.600		
Cutoff 2 (c_2)	−2.231	0.524		
Cutoff 3 (c_3)	0.634	0.483		

same, regardless of which set of responses from the University of Florida are used. Majorities of extensionists in the three-state region indicate that their clients can use climate forecasts to improve planting schedules, irrigation management, harvest planning, variety or crop selection, and nutrient management (Table 2). A majority might also think that their clients can use forecasts to improve land allocation; the statistical evidence is weak but stronger if one uses the follow-up responses from Florida (Table 2).

Parameter estimates and standard errors in the logit probabilities of an extensionist thinking people with whom she works can use climate forecasts to improve the six most selected managerial activities are presented in Table 5. As indicated by the scaled R^2s, conditional models incorporate 7.1% to 21.1% of the information about the managerial activities that an extensionist's clients could improve with climate forecasts (Table 5). The p values associated with the chi-squared statistics for the tests of nonzero effects of characteristics of an extensionist and her clientele range from 0.0687 to 0.000 021 in five of the six models (Table 5). Thus, each model of conditional probability, except the one for irrigation management, is more informative than an unconditional model estimated with a sample proportion.

Extensionists who work with field crop producers are more likely to think that their clients could use climate forecasts to improve plant scheduling, harvest planning, variety or crop selection, nutrient management, and land allocation (Table 5). The probabilities that such an extensionist's clientele could use the forecasts to improve these five managerial activities substantially increase. The lowest and highest mean increases are, with rounding, 13.5 percentage points for planting schedules and 23.1 percentage points for harvest planning and land allocation (Table 6).

Three other types of production, if relevant to an extensionist's work, also significantly affect her assessments of whether her clients can use forecasts to improve specific managerial activities (Table 5). In particular, if greenhouse and nursery production is relevant, the probability that she thinks her clients could improve irrigation management increases, on average, 14.2 percentage points (Table 6). If cattle or forage production is relevant, the probability that she thinks her clients can improve their land allocation increases, on average, 15.7 percentage points (Table 6). However, if she works with perennial fruit producers, the probability that she thinks her clients can improve planting schedules decreases, on average, 14.9 percentage points (Table 6).

The proportion of extension personnel who think their clients can use climate forecasts to improve various managerial activities also significantly increases if their clients have large farms or if they personally manage a farm (Table 5). For example, the proportion of extension personnel who think their clients can use climate forecasts to improve crop or varietal selection increases, on average, 16.5 percentage points, if the average size of their clientele's farms exceeds 200 acres (Table 6). Also,

TABLE 4. Mean effects ($n = 202$) of at least 7 years of extension experience and the relevance of production of various types of crops to the work of an extensionist on probability that she 1) strongly disagrees or disagrees, 2) neither agrees nor disagrees, 3) agrees, or 4) strongly agrees that farmers are interested in using climate forecasts.

Variable (k)	$\bar{\hat{P}}_1^k - \bar{\hat{P}}_1^{\sim k}$	$\bar{\hat{P}}_2^k - \bar{\hat{P}}_2^{\sim k}$	$\bar{\hat{P}}_3^k - \bar{\hat{P}}_3^{\sim k}$	$\bar{\hat{P}}_4^k - \bar{\hat{P}}_4^{\sim k}$
OVER6YREXP	−0.031	−0.079	0.026	0.084
FIELDCROP	−0.025	−0.073	0.020	0.078
VEGETABLE	0.027	0.069	−0.017	−0.079
CATTLEFORAGE	0.029	0.075	−0.022	−0.082

TABLE 5. Parameter estimates (and standard errors) in logit model of the probability that an extensionist's clients can use climate forecasts to improve a particular managerial activity (n = 199).

Variable	Planting schedule	Irrigation management	Harvest planning	Variety or crop selection	Nutrient management	Land allocation
CONSTANT	1.477[c] (0.684)	0.800 (0.552)	0.298 (0.530)	−0.624 (0.537)	0.400 (0.519)	−1.599[a] (0.556)
NCAROLINA	0.146 (0.489)	−0.748[c] (0.404)	0.016 (0.385)	0.062 (0.389)	−0.162 (0.380)	0.560 (0.398)
SCAROLINA	−0.449 (0.658)	0.007 (0.627)	0.571 (0.617)	0.608 (0.619)	−0.225 (0.560)	0.516 (0.607)
NONAGENTSC	−1.261[c] (0.750)	−0.305 (0.727)	−1.146 (0.747)	−1.592[b] (0.778)	−0.716 (0.695)	−0.167 (0.737)
MALE	−0.416 (0.523)	−0.278 (0.429)	0.023 (0.427)	−0.186 (0.427)	0.345 (0.416)	−0.203 (0.421)
BIGCLIENTFARM	0.651 (0.500)	0.677[c] (0.396)	0.662[c] (0.395)	0.838[b] (0.397)	0.440 (0.372)	0.203 (0.381)
OWNCOMFARM	0.126 (0.435)	0.081 (0.344)	0.240 (0.354)	0.992[a] (0.362)	−0.098 (0.337)	0.739[b] (0.342)
OVER6YREXP	−0.226 (0.467)	−0.188 (0.379)	−0.454 (0.389)	−0.112 (0.381)	−0.746[c] (0.383)	0.498 (0.376)
FIELDCROP	1.012[b] (0.505)	−0.025 (0.392)	1.129[a] (0.400)	0.890[b] (0.395)	0.700[c] (0.383)	1.067[a] (0.385)
VEGETABLE	0.083 (0.481)	0.559 (0.414)	−0.165 (0.401)	0.005 (0.404)	−0.601 (0.396)	0.176 (0.402)
CATTLEFORAGE	0.102 (0.458)	0.321 (0.365)	−0.014 (0.370)	0.239 (0.371)	0.525 (0.343)	0.765[b] (0.361)
NURSERYGH	0.896 (0.472)	0.705[c] (0.386)	0.233 (0.376)	0.510 (0.388)	0.202 (0.393)	−0.036 (0.386)
PERENFRUITNUT	−1.028[c] (0.499)	−0.441 (0.423)	−0.335 (0.403)	0.049 (0.408)	0.127 (0.390)	0.132 (0.412)
Scaled R^2	0.149	0.071	0.128	0.196	0.099	0.211
X_a^2	29.63	14.33	25.78	39.98	19.91	43.23
$\Pr[X^2(12) \geq X_a^2]$	0.0032	0.2799	0.0115	0.000 073	0.0687	0.000 021

[a] $p \leq 0.01$;
[b] $p \leq 0.05$;
[c] $p \leq 0.10$

if extension personnel themselves manage at least two acres of agricultural production, the proportion of personnel who think their clients could use climate forecasts to improve crop or varietal selection increases 19.6 percentage points (Table 6).

c. *Which types of farmers are likely to be able to use climate forecasts to be successful?*

Vegetable producers, row crop farmers, and orchard growers were the first, second, and third most frequently selected types, regardless of which data from Florida are used (Table 2). Nursery operators and livestock producers were, respectively, the fourth and fifth most frequently selected types of farmers, if 2004 data from Florida are used, and the fifth and fourth most selected types, if the 2009 data from Florida are used (Table 2). Majorities of extension personnel in the Carolinas and Florida think vegetable farmers, row crop farmers, orchard growers, nursery operators, and livestock managers are likely to be able to use climate forecasts to be more successful (Table 2).[5] Moreover, according to tests based on the square root of McNemar's statistic (Conover 1999), vegetable producers are more likely than row crop farmers, who are more likely than orchard growers, nursery operators, or livestock producers, to be assessed by extension personnel as likely to be able to use climate forecasts to be more successful.

Parameter estimates and standard errors for variables in the logit models of the probabilities that an extensionist indicates which type of farmer is likely to be able to use climate forecasts to be more successful are reported in Table 7. The scaled R^2s indicate that the conditional models incorporate 6.0% to 20.6% of the

TABLE 6. Mean effects (n = 199) of crop relevance, own commercial farm, at least seven years of extension experience, and the size of clientele's farm on the probability that an extensionist's clients can use climate forecasts to improve a particular managerial activity.

Activity (a)	Variable (k)	$\bar{\hat{P}}_{I_a}^{k}$	$\bar{\hat{P}}_{I_a}^{\sim k}$	$\bar{\hat{P}}_{I_a}^{k} - \bar{\hat{P}}_{I_a}^{\sim k}$
Planting schedules	FIELDCROP	0.873	0.738	0.135
	PERENFRUITNUT	0.691	0.840	−0.149
Irrigation management	BIGCLIENTFARM	0.754	0.618	0.136
	NURSERYGH	0.756	0.614	0.142
Harvest planning	BIGCLIENTFARM	0.742	0.611	0.132
	FIELDCROP	0.786	0.555	0.231
Crop or variety selection	BIGCLIENTFARM	0.716	0.551	0.165
	OWNCOMFARM	0.729	0.533	0.196
	FIELDCROP	0.713	0.532	0.181
Nutrient management	OVER6YREXP	0.559	0.714	−0.155
	FIELDCROP	0.688	0.534	0.154
Land allocation	OWNCOMFARM	0.637	0.484	0.153
	FIELDCROP	0.673	0.442	0.231
	CATTLEFORAGE	0.639	0.481	0.157

[5] A majority no longer might think nursery operators are likely (FollowUpF09 in Table 2) because Florida's proportion of respondents who selected nursery operators fell (Breuer et al. 2010).

TABLE 7. Parameter estimates (standard errors) in logit model of the probability that an extensionist indicates a type of farmer is likely to be able to use climate forecasts to be more successful (n = 200).

Variable	Row crop farmers	Vegetable farmers	Livestock managers	Nursery operators	Orchard growers
CONSTANT	0.947 (0.607)	1.654[b] (0.688)	−0.143 (0.534)	0.832 (0.560)	0.326 (0.524)
NCAROLINA	0.883[c] (0.453)	−0.182 (0.516)	0.066 (0.395)	−1.088[b] (0.423)	−0.272 (0.387)
SCAROLINA	0.900 (0.688)	−0.559 (0.716)	0.695 (0.594)	−0.951[c] (0.586)	0.248 (0.587)
NONAGENTSC	−1.002 (0.816)	−0.128 (0.804)	−1.386[c] (0.724)	−0.409 (0.691)	0.268 (0.524)
MALE	−0.247 (0.505)	0.017 (0.529)	−0.180 (0.431)	0.698 (0.425)	0.448 (0.416)
BIGCLIENTFARM	−0.328 (0.489)	0.137 (0.505)	0.071 (0.387)	0.245 (0.374)	0.151 (0.374)
OWNCOMFARM	−0.218 (0.424)	0.073 (0.450)	0.214 (0.349)	−0.240 (0.339)	−0.060 (0.340)
OVER6YREXP	−0.149 (0.448)	−0.417 (0.513)	0.544 (0.373)	−0.184 (0.380)	−0.176 (0.378)
FIELDCROP	2.062[a] (0.558)	0.574 (0.511)	0.133 (0.403)	−0.102 (0.382)	−0.576 (0.389)
VEGETABLE	−0.694 (0.452)	1.086[c] (0.568)	−1.227[a] (0.412)	−0.828[c] (0.431)	−0.253 (0.411)
CATTLEFORAGE	0.333 (0.445)	−0.291 (0.457)	1.282[a] (0.378)	−0.364 (0.358)	−0.232 (0.353)
NURSERYGH	−0.968[b] (0.430)	−0.011 (0.504)	−0.301 (0.371)	1.615[a] (0.431)	0.417 (0.386)
PERENFRUITNUT	0.446 (0.448)	0.104 (0.561)	0.583 (0.407)	−0.017 (0.436)	1.180[a] (0.438)
Scaled R^2	0.206	0.060	0.171	0.173	0.112
X_m^2	41.66	11.91	35.12	35.35	22.63
$\Pr[X^2(12) \geq X_m^2]$	0.000 038	0.453	0.000 45	0.000 41	0.031

[a] $p \leq 0.01$;
[b] $p \leq 0.05$;
[c] $p \leq 0.10$

information of an extensionist's assessment (Table 7). The p values associated with the chi-square statistics for the tests of nonzero effects of characteristics of an extensionist and her clientele in the four statistically significant models range from 0.0310 to 0.000 038 (Table 7). Thus, each conditional model, except the one for vegetable growers, is more informative than an unconditional model estimated with a sample proportion.

In general, the probability that an extensionist thinks a farmer who produces a particular type of commodity is likely to be able to use climate forecasts to be more successful increases significantly if the type of production is also relevant to the extensionist's work (Table 7). The lowest mean increase is 12.4 percentage points in the probability of a positive assessment about vegetable farmers if vegetable production is relevant to the extensionist and the highest mean increase is 31.6 percentage points for a positive assessment about nursery operators if greenhouse and nursery production is relevant to the extensionist's work (Table 8).

7. Discussion

a. Effects of the state and university where an extensionist works and survey year on assessments

Substitution of Florida's 2009 data for its 2004 data does not significantly change most proportions and changes only one statistical inference about the assessments of majorities of extension personnel in the three-state region. Moreover, 10 of the 12 models of conditional probabilities are statistically unaffected (for α = 0.05) if the extensionist works in the Carolinas. However, an extensionist in South or North Carolina is significantly less likely than one in Florida to agree or strongly agree that farmers are interested in using climate forecasts and think that nursery operators are likely to be able to use climate forecasts to be more successful.

These exceptions might be artifacts of Florida's 2004 data. The population proportions of the University of Florida's extensionists who would agree or strongly agree and select nursery operators are statistically lower in 2009 than 2004.[6] One reason why the proportion who would at least agree has fallen is that the proportion of the university's extension agents who have less than 7 years of experience in extension has risen.[7] The probability of an extensionist at least agreeing decreases 11 percentage points if the extensionist is inexperienced (Table 4).

[6] Proportions of Florida's follow-up responses for these two assessments in 2009 were lower than proportions of the baseline responses in 2004. As a result, the proportions of responses for farmer interest and nursery operators are also lower if the follow-up rather than baseline data from Florida are used (Table 2). The conclusion about decreases in population proportions is based on a p value < 0.05, under H_o, $p_{04} \leq p_{09}$, of observing a value of an asymptotically standard normal random variable larger than $(\hat{p}_{04} - \hat{p}_{09})/\sqrt{\hat{p}(1-\hat{p})(1/n_{04} + 1/n_{09})}$, where $\hat{p}_{04}$ and $\hat{p}_{09}$ are the sample proportions in 2004 and 2009 and $\hat{p} = \hat{p}_{04}n_{04}/(n_{04} + n_{09}) + \hat{p}_{09}n_{09}/(n_{04} + n_{09})$.

[7] The proportions of Florida's respondents who had less than 7 years of experience in extension were 23.3% in 2004 and 45.6% in 2009 and presumably reflect retirements and new hires. An asymptotic z statistic similar to the one above was calculated to test for the rise.

TABLE 8. Mean effects ($n = 200$) of the relevance to an extensionist of various types of crop production to her work on the probability that she indicates that a farmer who produces a particular type of crop is likely to be able to use climate forecasts to be more successful.

Type of farm manager (m)	Variable (k)	$\overline{\hat{P}}^{k}_{S_m}$	$\overline{\hat{P}}^{\sim k}_{S_m}$	$\overline{\hat{P}}^{k}_{S_m} - \overline{\hat{P}}^{\sim k}_{S_m}$
Vegetable farmers	VEGETABLE	0.918	0.794	0.124
Row crop farmers	FIELDCROP	0.920	0.632	0.288
	NURSERYGH	0.669	0.818	−0.149
Orchard growers	PERENFRUITNUT	0.792	0.554	0.238
Nursery operators	NURSERYGH	0.804	0.488	0.316
	VEGETABLE	0.505	0.667	−0.162
Livestock producers	CATTLEFORAGE	0.750	0.484	0.266
	VEGETABLE	0.435	0.687	−0.252

A second reason for the decrease in the proportion who would at least agree and a reason for the decrease in the proportion who would select nursery operators might be that extensionists acquired additional information that was uncorrelated with variables in the two conditional models and that lowered their expectations about the net benefits of climate forecasts to farmers and, in particular, nursery operators. If the 2009 data from Florida could have been used to reestimate the conditional models, the negative effects of the Carolina dummy variables or the positive effects of the constant terms on these two assessments might have diminished to the extent that the new information caused the proportions in Florida to fall.

b. *Effects of at least 7 years of experience in extension on assessments*

The more on-the-job experience that extensionists have, the more likely they can judge the value to farmers of using climate forecasts and know how to communicate and interpret the forecasts to their clients (e.g., Crane et al. 2010). For these possible reasons, extensionists who have worked at least 7 years in their jobs are more likely than ones who have not to at least agree that farmers are interested in using climate forecasts. However, although seasonal climate forecasts have been published for 15–25 years (e.g., NWS 2003), dissemination of recommendations about how to use climate information for specific types of managerial activities or crops in the Southeast is a relatively recent phenomenon. Thus, although extensionists with at least 7 years of on-the-job experience might know more about farmers and how to work with them than their less-experienced colleagues in the three-state region, they might not know more about which managerial activities their clients can improve with climate forecasts and which types of farmers are likely to be able to use the forecasts to be more successful.

The one exception is that experienced extensionists are less likely to assess that their clients can use forecasts to improve nutrient management. Experienced extensionists or their clients might be more likely than inexperienced ones or their clients to view nutrient management as a costly government-promoted best management practice to reduce water pollution (Brant 2003).

Years in extension was positively correlated with age and more directly measures job experience than age does. Age never affected assessments in preliminary versions of our models.

c. *Effects of engagement in commercial agriculture and contact with farmers on assessments*

Extensionists who engage in commercial agriculture span boundaries (e.g., Lubell et al. 2014) and are more likely to have hands-on experience with farm management than those who do not. For this possible reason, they might be better able to assess benefits and costs to farmers of using climate forecasts to improve their selection of crops or varieties and allocation of land to crops. Extension associates and specialists in South Carolina are less likely than agents in the three-state region to make positive assessments in 4 of the 12 models ($p \leq 0.1$) because they usually have less contact with farmers than agents do. As a result, nonagents might have less practical or different information about farmers and be less inclined to select options in the survey.

d. *Effects of an extensionist working with field crop producers on assessments*

If field crop production is relevant to an extensionist, why are most of her assessments more likely to be favorable? Yields of rain-fed field crops are more likely than yields of irrigated field crops to respond to climate variability (e.g., Klocke et al. 2007). Field crops are significantly less likely than other types of crops to be irrigated in the Carolinas and Florida.[8] Producers of rain-fed crops tend to be more concerned about climate variability and more interested in climate forecasts than producers of mostly irrigated, high-value crops (Crane et al. 2010; Jagtap et al. 2002). Thus, actual or perceived

[8] For example, farmers in the three-state region irrigated 4.5% of the harvested area of the five highest-valued field crops but 85.5% of orchard area and 57.6% of harvested area of vegetables in 2007 (NASS 2014).

increases in yields from the use of climate forecasts for various managerial activities might be larger for field crops than other crops. An extensionist who works with field crop producers is more likely than one who does not, for these possible reasons, to think that farmers in her area would be interested in using forecasts and that field crop producers could use them for greater success and, in particular, for improvement of land allocation, variety or crop selection, planting schedules, nutrient management, and harvest planning.

Most advisors of corn producers in four upper Midwestern states of the United States make similar assessments; they think that corn producers can use historical weather or trend forecasts to plan planting and harvesting, tailor hybrid selection, allocate field assignments and crop rotations, and improve irrigation planning (Prokopy et al. 2013). Anecdotal evidence from the southeastern United States indicates that field crop producers have begun to use climate forecasts to improve variety or crop selection and land allocation (e.g., Langcuster 2013; Crane et al. 2010).

e. *Effects of working with producers of other types of commodities on assessments*

If an extensionist works with producers of a particular type of commodity, she probably knows more than one who does not work with them about whether benefits of climate forecasts exceed costs to the producers and whether her own help could raise the net benefits. Thus, the greater likelihood of an extensionist who works with producers of a particular type of commodity assessing that those producers could use forecasts to be more successful—significant in assessments about producers of all four types of commodities in addition to field crops—might mean a greater likelihood that she perceives the benefits do or could exceed the costs to them.

The negative and separate effects of an extensionist's working with cattle forage producers and vegetable producers on her assessment of farmer interest in climate forecasts are still consistent with the positive effects of her working with these types of producers on her assessments of whether her clients are likely to be able to use the forecasts to be successful. Livestock managers and vegetable farmers can be capable of but not interested in using forecasts for success. Moreover, an extensionist who works with vegetable farmers might be less likely to agree that farmers in her region are interested because she thinks vegetable farmers should address marketing and costs related to infrastructure (Hildebrand et al. 1999).

What might explain why extensionists who work with vegetable producers are less likely than other extensionists to indicate that nursery operators and livestock managers could use climate forecasts to be more successful? Growers of vegetables in the three-state region have had limited or no access to federal crop insurance. For example, federal crop insurance was not available to growers of five of the six highest-valued types of vegetables in South Carolina in 2010 and 2011 (NASS 2012; RMA 2012, 2011), seven of the eight highest-valued types of vegetables in North Carolina in 2009 (NCDACS-NASS 2011; RMA 2010), three of the nine highest-valued types of vegetables in Florida during 2003–04 (FASS 2006; RMA 2005), and no other types of vegetables in these states and years.

In contrast, nursery operators and livestock managers in the Carolinas and Florida have had access to various public or private sector means to reduce yield and revenue risk. In particular, "[t]he nursery program is one of the largest Federal crop insurance products after the main program commodities" (RMA 2013, p. 18). Nursery growers insured 85% of the total value of their field grown and container products in 2009 (RMA 2013). Livestock managers in the Southeast and elsewhere have been able to trade futures contracts for live cattle and feeder cattle through the Chicago Mercantile Exchange Group to hedge their risks. Also, the USDA has supported prices for dairy farmers since 1949 (FSA 2011). Moreover, federal insurance for owners of pasture, rangeland, and forage crops was available as a pilot program in North Carolina (RMA 2009) and South Carolina (RMA 2011) at least 1 year before the baseline surveys were conducted, although not in Florida during 2004 (RMA 2005).

Crop insurance often crowds out farmer use of other risk-mitigating inputs (e.g., Smith and Glauber 2012) and reduces the simulated value of ENSO forecasts to a typical row crop farmer in North Florida (Cabrera et al. 2007). An extensionist with vegetable-growing clients might be more likely than one without them to perceive that nursery and livestock producers have substantially more access than her clients to crop insurance and futures markets and, as a result, these producers have weaker incentives than her clients to mitigate risk with climate forecasts.

A similar conjecture could explain why extensionists who work with nursery greenhouse growers are less likely than ones who do not to think that row crop farmers could use climate forecasts to be more successful. Although federal insurance is widely available to nursery crop producers in the Southeast and elsewhere, it "is sold mostly at the CAT [catastrophic] level of insurance" (RMA 2013, p. 18). Thus, the nursery sector's share of insured liabilities is less than the nursery sector's share of crop revenue (Lee and Sumner 2013). In contrast, row crop farmers in Florida and the Carolinas insured 95.5%, 85.3%, 83.2%, and 79.7% of their areas planted with cotton, soybeans, peanuts, and corn during 2008–11 (RMA 2015). Also, the government does not support prices of nursery products. In contrast, producers of field crops had received additional income from direct and countercyclical price payments and the Average Crop Revenue Election program through 2014 and now receive income support from the Price Loss Coverage and Agricultural Risk Coverage programs, which are distinct from federal crop insurance (Chite 2014). An extensionist who works with nursery greenhouse producers might be more likely than one who does not to perceive that row crop farmers benefit more than nursery greenhouse producers from revenue-supporting or risk-reducing government programs and thus have weaker incentives than her clients to use climate forecasts.

If an extensionist works with greenhouse nursery growers, she is more likely than one who does not to think her clients could use climate forecasts to improve irrigation management for the possible reason that they are among the types of farmers who most extensively irrigate[9] and greenhouse nursery crops are relatively high value. The benefits of accessing information increase with the value of the irrigated crop (e.g., Frisvold and Deva 2012).

Perennials, particularly perennial grasses, are ubiquitous in most pastures and hayfields for cattle in the southeastern United States. (e.g., Hancock et al. 2015). Also, forages in pastures and hayfields are among the plants least likely to be irrigated in the Southeast (e.g., NASS 2014). However, portions of perennial pastures, particularly on large ranches, are renewed, fertilized, or rehabilitated each year. Moreover, some livestock producers (re)plant pastures with annuals on a seasonal basis (e.g., Hancock et al. 2015). El Niño years are usually good for planting and establishment of cool-season grasses and harvesting an abundant amount of hay in the spring (Fraisse et al. 2006). Thus, an extensionist who works with cattle or forage producers might think that her clients can use climate forecasts to improve their allocation of land for forage or other crops because some cattle producers seasonally decide, particularly during winters, how much forage to grow for their herds (Jagtap et al. 2002). However, she is not more likely than others to think that her clients can use the forecasts to improve the other managerial activities because the activities are infrequently undertaken or not relevant for livestock production.

Perennial fruit and nut trees have economic lives of 10–30 years and thus are infrequently planted. Moreover, forecasts of climate beyond an upcoming growing season are not necessarily reliable or available. Thus, benefits to perennial fruit and nut producers who would consider using climate forecasts for planting schedules might be low. An extensionist who works with perennial fruit or nut producers might be more likely than an extensionist who does not work with them to perceive relatively low benefits and, for this possible reason, also be less likely to think that her clients could use climate forecasts to improve planting schedules.

f. Effects of clientele with above-average-sized farms on assessments

An extensionist whose clients have farms larger than 200 acres is more likely than one whose clients have smaller farms to think her clients can use climate forecasts to improve variety or crop selection, irrigation management, and harvest planning for the possible reason that the expected net benefits to farmers of the forecasts for these activities increase with farm size. In particular, the cost of utilizing the forecasts does not vary much with farm size or harvest (e.g., Frisvold and Deva 2012); the cost is primarily quasi fixed. If a farmer's use of the forecasts improves his decision-making, then the expected benefit of the forecasts increases with the scale of production (e.g., Feder and Slade 1984). The benefit of utilizing the forecasts will exceed, beyond some farm size, the quasi-fixed cost. If the cost is high enough, the net benefits only become positive for large farms (e.g., Breuer et al. 2008). Also, the net benefits to an extensionist of interpreting the forecasts to farmers should, for similar reasons, increase with farm size.

Various findings are consistent with these arguments. For example, the larger is the sales class of his farm, the more likely a farmer in New Mexico or Arizona relies on irrigation information from any source and a farmer in Arizona relies on the information from extensionists (Frisvold and Deva 2012). Also, the probability that information about the major El Niño of 1997/98 was more important than information about ENSO phases in previous years increased with the size of a cereal or oilseed producer's farm in Pergamino, Argentina (Letson et al. 2001).

However, planting schedules and crop rotation tend to be rigidly scheduled on large farms with specialized equipment and buildings, and thus operators of large farms have less flexibility to alter these activities in response to climate forecasts (Crane et al. 2010; Breuer et al. 2008). Inflexibility reduces the benefits of information (Mjelde et al. 1988). This inflexibility might explain why an extensionist whose clients have large farms is as likely as one whose clients do not to think that her clients could use climate forecasts to improve planting schedules and land allocation. A relevant finding is that the sales class of a crop producer in Arizona has no effect on his use of

[9] For example, they irrigated 80.3% of areas under protection and in the open for flowers, nursery stock, and other horticultural specialties in the three-state region in 2009 (NASS 2010).

weather data for the timing of plantings (Frisvold and Murugesan 2013). Also, farm sales have no effect on the influence that ''long-term'' forecasts have on ''agronomic decisions'' (Artikov et al. 2006). Moreover, farm size has no effect on the probability that advisors in the upper Midwest consider weather and climate information in advice that they give corn producers about a ''planting/harvest schedule'' (Haigh et al. 2015).

8. Conclusions

An extensionist's job tenure, work with producers of various types of commodities, production experience in agribusiness, and clientele's farm size can significantly affect her assessments of whether, how, and which farmers in the Carolinas and Florida would use climate forecasts. For example, the conditional probabilities of an extensionist thinking that producers of each of the five different types of commodities can use climate forecasts to be more successful rise 12.4 to 31.6 percentage points, on average, if producers of the commodities are among her clients (Table 8). Incidentally, gender and thus any gender-specific attitude or job norm does not matter here.

These and other conditional mean effects depend on parameter values that are estimated with baseline data, which are reference points for future data. Parameter values do not necessarily change over time and estimation of them in correctly specified models remains unbiased, even if measured characteristics cause population proportions, or unconditional probabilities, to change.

However, at least some parameter values and estimates thereof are subject to change. For example, the RMA expanded coverage, through Whole-Farm Revenue Protection, of subsidized insurance for fruit and vegetable production in 2015 to pilot counties and in 2016 to all counties of the three-state region (e.g., Karst 2015; USDA 2014). Extensionists who work with vegetable producers might change their assessments because of the expanded coverage and thus parameter values associated with having such clients might change.

Our explanations of the conditional mean effects are also provisional. Most of them entail implicit hypotheses that merit testing, at least for southeastern agriculture. For example, the extent to which crop insurance substitutes for or, as others argue (e.g., Meza et al. 2008), complements climate information in risk mitigation is an important matter to investigate.

Nonetheless, the conditional assessments almost always provide more nuanced information than unconditional ones about potential adoption by farmers of climate forecasts in the three-state region. For example, the proportion of extensionists who think that vegetable farmers could use climate forecasts for more success exceeds the proportion of them who think that row crop farmers could. However, a positive assessment of row crop farmers being able to use them for more success is as likely as a positive assessment of vegetable farmers being able to do so if the assessment is conditional on an extensionist working with the respective groups of farmers (Table 8). In fact, increases in conditional probabilities of positive assessments occur most often, in 7 of the 12 models, and are among the largest if an extensionist works with producers of field crops.

These positive effects might provide reasons for developers of decision support tools to focus on five managerial activities of field crop producers. However, the diminished optimism that extensionists who work with nursery greenhouse growers have about row crop producers being able to use climate forecasts for more success might raise concerns with developers about their focus. This diminished optimism and the relative pessimism that extensionists who work with vegetable producers have about livestock managers and nursery operators being able to use forecasts for more success at least raise questions that key informants, focus group members, or new survey respondents might answer as coproducers of such tools in the future.

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APPENDIX

Survey Details, Probabilities, Likelihood Functions, Test Statistics, and Effects of Indicator Variables

Survey questions (Q) and answer choices (AC) by state are presented in Table A1.

Based on Train (2009), the ordered logit probability that extensionist r, in response to the statement that

TABLE A1. Numbered questions (Q) and answer choices (AC) from survey by state.

Number	Florida	North Carolina	South Carolina
Q1	Agricultural producers (farmers, forest owners, livestock growers) in my region are interested in using climate forecasts.	In my opinion, growers and producers (including forest owners, livestock producers, etc.) in my county are interested in using climate forecasts.	In my opinion, growers and producers (including forest owners, livestock producers, etc.) in my region are interested in using climate forecasts.
AC1	Disagree strongly, disagree, agree, agree strongly, neither agree or disagree	Strongly agree, agree, neither agree nor disagree, disagree, strongly disagree	
Q2	People I work with can use climate forecasts to improve… (Check all that apply.)		
AC2	Allocation of land to crops or activities, planting schedules, spacing or stand density, variety or crop selection, marketing, irrigation management, nutrient management, waste management, harvest planning, labor management, other: _______	Planting schedules, allocation of land to crops or activities, labor management, harvest planning, waste management, nutrient management, irrigation management, marketing, variety or crop selection, spacing or stand density, integrated pest management, other: _______ [Selections of integrated pest management were recategorized as other to enable consistent comparisons with data from the Florida survey.]	
Q3	Who is likely to be able to use climate forecasts to be more successful? (Check all that apply.)		
AC3	Livestock producers, orchard growers, vegetable farmers, row crop farmers, nursery operators, landscapers, tourist industries, forest managers/owners, extension agents, aquaculture producers, water resources managers, emergency planners, other: _______	Row crop farmers, vegetable farmers, nursery operators, orchard growers, livestock (cattle, hog, poultry, etc.) producers, emergency planners, water resources managers, aquaculture producers, extension agents, forest managers/owners, tourism industries, landscapers, other: _______ [Responses about aquaculture producers, emergency planners, extension agents, forest managers/owners, landscapers, tourism industries, and water resource managers were not used for our analysis because they do not pertain to farmers or, at least, to conventional farmers.]	
Q4	How long have you been working in extension?	How long have you been involved in extension?	
AC4	Less than 1 year, 1 to 3 years, 4 to 6 years, more than 6 years		
Q5 and AC5	Which type of extension position, regardless of rank, do you have? (Check all that apply.) Extension associate, extension agent, extension specialist, other. [This question was not included in the Florida and North Carolina surveys.]		
Q6 and AC6	What is your gender? Female, male		
Q7	What is the average farm size of the producers you work with?		
AC7	Less than 2 acres, 2 to 10 acres, 11 to 80 acres, 81 to 200, more than 200 acres	Less than 2 acres, 2 to 10 acres, 11 to 80 acres, 81 to 200 acres, 201 to 500 acres, 501 to 1000 acres, more than 1000 acres	
Q8	If you are also a producer, how much land do you manage (lease or own)?	If you are also a producer, how much land do you manage (including leased or owned)?	How much land, if any, do you manage (including leased or owned) for agricultural production?
AC8	Less than 2 acres, 2 to 10 acres, 11 to 80 acres, 81 to 200 acres, more than 200 acres	Less than 2 acres, 2 to 10 acres, 11 to 80 acres, 81 to 200 acres, 201 to 500 acres, 501 to 1000 acres, more than 1000 acres	I am not an agricultural producer, less than 2 acres, 2 to 10 acres, 11 to 80 acres, 81 to 200 acres, 201 to 500 acres, 501 to 1000 acres, more than 1000 acres

TABLE A1. (*Continued*)

Number	Florida	North Carolina	South Carolina
Q9	Which of the following activities are relevant to your work? (Check all that apply.)		
AC9	Field crop production (i.e., soybean, corn, peanut), vegetable production (i.e., tomato, lettuce, melon), beef cattle, dairy cattle, greenhouse or nursery production, forage production, annual fruit production (i.e., strawberries), perennial fruit or nut production, timber production, water quality, other: ______	Field crop production (e.g., corn, cotton, peanut, soybean, tobacco, wheat), vegetable production (e.g., cucumber, tomato, bell pepper, sweet potato), beef cattle, dairy cattle, hogs, poultry, greenhouse or nursery production, forage production, annual fruit production (e.g., strawberries), aquaculture, perennial fruit or nut production (e.g., pears [NC version] peaches [SC version], blueberries), timber/Christmas tree production, turfgrass/landscape, water quality, other: ______ [If hogs, poultry, aquaculture, or turfgrass/landscape was selected, the response was reclassified as other to make data from the Carolinas comparable to data from Florida.]	

farmers are interested in using climate forecasts strongly disagrees or disagrees, is

$$P_{Y1_r} \equiv \Pr(Y1_r = 1) = \Pr(U_r^i \le c_1) = \Pr(\mathbf{X}_r\boldsymbol{\beta} + \varepsilon_{Y_r} \le c_1)$$
$$= \Pr(\varepsilon_{Y_r} \le c_1 - \mathbf{X}_r\boldsymbol{\beta}) = \frac{\exp(c_1 - \mathbf{X}_r\boldsymbol{\beta})}{1 + \exp(c_1 - \mathbf{X}_r\boldsymbol{\beta})},$$

neither disagrees nor agrees is

$$P_{Y2_r} \equiv \Pr(Y2_r = 1) = \Pr(c_1 < U_r^i \le c_2)$$
$$= \Pr(c_1 < \mathbf{X}_r\boldsymbol{\beta} + \varepsilon_{Y_r} \le c_2)$$
$$= \frac{\exp(c_2 - \mathbf{X}_r\boldsymbol{\beta})}{1 + \exp(c_2 - \mathbf{X}_r\boldsymbol{\beta})} - \frac{\exp(c_1 - \mathbf{X}_r\boldsymbol{\beta})}{1 + \exp(c_1 - \mathbf{X}_r\boldsymbol{\beta})},$$

agrees is

$$P_{Y3_r} \equiv \Pr(Y3_r = 1) = \Pr(c_2 < U_r^i \le c_3)$$
$$= \Pr(c_2 < \mathbf{X}_r\boldsymbol{\beta} + \varepsilon_{Y_r} \le c_3)$$
$$= \frac{\exp(c_3 - \mathbf{X}_r\boldsymbol{\beta})}{1 + \exp(c_3 - \mathbf{X}_r\boldsymbol{\beta})} - \frac{\exp(c_2 - \mathbf{X}_r\boldsymbol{\beta})}{1 + \exp(c_2 - \mathbf{X}_r\boldsymbol{\beta})},$$

and strongly agrees is

$$P_{Y4_r} \equiv \Pr(Y4_r = 1) = \Pr(U_r^i > c_3) = \Pr(\mathbf{X}_r\boldsymbol{\beta} + \varepsilon_{Y_r} > c_3)$$
$$= 1 - \Pr(\varepsilon_{Y_r} \le c_3 - \mathbf{X}_r\boldsymbol{\beta}) = 1 - \frac{\exp(c_3 - \mathbf{X}_r\boldsymbol{\beta})}{1 + \exp(c_3 - \mathbf{X}_r\boldsymbol{\beta})}.$$

The probability that respondent r indicates that the people with whom she works could use climate forecasts to improve managerial activity a is

$$P_{I_{a,r}} \equiv P(I_{a,r} = 1) = P(UF_r^a > 0) = P(\mathbf{Z}_r\boldsymbol{\lambda}_a + \varepsilon_{I_{r,a}} > 0)$$
$$= P(\varepsilon_{I_{r,a}} > -\mathbf{Z}_r\boldsymbol{\lambda}_a) = P(\varepsilon_{I_{r,a}} \le \mathbf{Z}_r\boldsymbol{\lambda}_a) = \frac{\exp(\mathbf{Z}_r\boldsymbol{\lambda}_a)}{1 + \exp(\mathbf{Z}_r\boldsymbol{\lambda}_a)}.$$

The probability that respondent r indicates that a type-m farm manager is likely to be able to use climate forecasts to be more successful is

$$P_{S_{m,r}} \equiv P(S_{m,r} = 1) = P(UF_r^m = \mathbf{Z}_r\boldsymbol{\lambda}_m + \varepsilon_{S_{m,r}} > 0)$$
$$= P(\varepsilon_{S_{m,r}} > -\mathbf{Z}_r\boldsymbol{\lambda}_m) = P(\varepsilon_{S_{m,r}} \le \mathbf{Z}_r\boldsymbol{\lambda}_m)$$
$$= \frac{\exp(\mathbf{Z}_r\boldsymbol{\lambda}_m)}{1 + \exp(\mathbf{Z}_r\boldsymbol{\lambda}_m)}.$$

The unconstrained likelihood functions are $L_Y = \prod_{r=1}^{202}(P_{Y1_r})^{Y1_r}(P_{Y2_r})^{Y2_r}(P_{Y3_r})^{Y3_r}(P_{Y4_r})^{Y4_r}$, $L_{I_a} = \prod_{r=1}^{199}(P_{I_{a,r}})^{I_{a,r}}(1-P_{I_{a,r}})^{1-I_{a,r}}$, and $L_{S_m} = \prod_{r=1}^{200}(P_{S_{m,r}})^{S_{m,r}}(1-P_{S_{m,r}})^{1-S_{m,r}}$. Let L_Y^c be the maximized value of the likelihood function if all parameters except the three cut points are constrained to be zero. Similarly, let $L_{I_a}^c$ and $L_{S_m}^c$ be the maximized values of the respective likelihood functions if all parameters except the constant c_a or c_m are also constrained to be zero. The scaled R^2s are $1-(\ln L_Y/\ln L_Y^c)^{-(2/N)\ln L_Y^c}$, $1-(\ln L_{I_a}/\ln L_{I_a}^c)^{-(2/N)\ln L_{I_a}^c}$, and $1-(\ln L_{S_m}/\ln L_{S_m}^c)^{-(2/N)\ln L_{S_m}^c}$ for the respective models. The test statistics for the models are $-2[\ln(L_Y^c)-\ln(L_Y)]$, $-2[\ln(L_{I_a}^c)-\ln(L_{I_a})]$, and $-2[\ln(L_{S_m}^c)-\ln(L_{S_m})]$ and are distributed χ^2 with 12 degrees of freedom (e.g., Train 2009).

Let $\mathbf{X}_r^{\sim k}$ be a 1×14 vector of variables that represents all but the kth characteristic of respondent r or her clientele, let $\hat{\boldsymbol{\beta}}^{\sim k}$ be a 14×1 vector of parameter estimates except the kth one, and let $\hat{\beta}_k$ be the parameter estimate for the kth variable. The effects of the kth indicator variable on the estimated ordered logit probabilities for the rth respondent are

$$\hat{P}_{Y1_r}^k - \hat{P}_{Y1_r}^{\sim k} = \frac{\exp(c_1 - \mathbf{X}_r^{\sim k}\hat{\boldsymbol{\beta}}^{\sim k} - \hat{\beta}_k)}{1+\exp(c_1 - \mathbf{X}_r^{\sim k}\hat{\boldsymbol{\beta}}^{\sim k} - \hat{\beta}_k)} - \frac{\exp(\mathbf{X}_r^{\sim k}\hat{\boldsymbol{\beta}}^{\sim k})}{1+\exp(\mathbf{X}_r^{\sim k}\hat{\boldsymbol{\beta}}^{\sim k})}$$

for strongly disagrees or disagrees,

$$\hat{P}_{Y2_r}^k - \hat{P}_{Y2_r}^{\sim k} = \left[\frac{\exp(c_2 - \mathbf{X}_r^{\sim k}\hat{\boldsymbol{\beta}}^{\sim k} - \hat{\beta}_k)}{1+\exp(c_2 - \mathbf{X}_r^{\sim k}\hat{\boldsymbol{\beta}}^{\sim k} - \hat{\beta}_k)} - \frac{\exp(c_1 - \mathbf{X}_r^{\sim k}\hat{\boldsymbol{\beta}}^{\sim k} - \hat{\beta}_k)}{1+\exp(c_1 - \mathbf{X}_r^{\sim k}\hat{\boldsymbol{\beta}}^{\sim k} - \hat{\beta}_k)}\right] - \left[\frac{\exp(c_2 - \mathbf{X}_r^{\sim k}\hat{\boldsymbol{\beta}}^{\sim k})}{1+\exp(c_2 - \mathbf{X}_r^{\sim k}\hat{\boldsymbol{\beta}}^{\sim k})} - \frac{\exp(c_1 - \mathbf{X}_r^{\sim k}\hat{\boldsymbol{\beta}}^{\sim k})}{1+\exp(c_1 - \mathbf{X}_r^{\sim k}\hat{\boldsymbol{\beta}}^{\sim k})}\right]$$

for neither disagrees nor agrees,

$$\hat{P}_{Y3_r}^k - \hat{P}_{Y3_r}^{\sim k} = \left[\frac{\exp(c_3 - \mathbf{X}_r^{\sim k}\hat{\boldsymbol{\beta}}^{\sim k} - \hat{\beta}_k)}{1+\exp(c_3 - \mathbf{X}_r^{\sim k}\hat{\boldsymbol{\beta}}^{\sim k} - \hat{\beta}_k)} - \frac{\exp(c_2 - \mathbf{X}_r^{\sim k}\hat{\boldsymbol{\beta}}^{\sim k} - \hat{\beta}_k)}{1+\exp(c_2 - \mathbf{X}_r^{\sim k}\hat{\boldsymbol{\beta}}^{\sim k} - \hat{\beta}_k)}\right] - \left[\frac{\exp(c_3 - \mathbf{X}_r^{\sim k}\hat{\boldsymbol{\beta}}^{\sim k})}{1+\exp(c_3 - \mathbf{X}_r^{\sim k}\hat{\boldsymbol{\beta}}^{\sim k})} - \frac{\exp(c_2 - \mathbf{X}_r^{\sim k}\hat{\boldsymbol{\beta}}^{\sim k})}{1+\exp(c_2 - \mathbf{X}_r^{\sim k}\hat{\boldsymbol{\beta}}^{\sim k})}\right]$$

for agrees, and

$$\hat{P}_{Y4_r}^k - \hat{P}_{Y4_r}^{\sim k} = \left[\frac{\exp(c_3 - \mathbf{X}_r^{\sim k}\hat{\boldsymbol{\beta}}^{\sim k})}{1+\exp(c_3 - \mathbf{X}_r^{\sim k}\hat{\boldsymbol{\beta}}^{\sim k})} - \frac{\exp(c_3 - \mathbf{X}_r^{\sim k}\hat{\boldsymbol{\beta}}^{\sim k} - \hat{\beta}_k)}{1+\exp(c_3 - \mathbf{X}_r^{\sim k}\hat{\boldsymbol{\beta}}^{\sim k} - \hat{\beta}_k)}\right]$$

for strongly agrees.

Let $\mathbf{Z}_r^{\sim k}$ be a 1×12 vector of all but the kth indicator variable. The effect of the kth variable on the probability that respondent r thinks her clients could use climate forecasts to improve activity a is $\hat{P}_{I_{a,r}}^k - \hat{P}_{I_{a,r}}^{\sim k} = [\exp(\mathbf{Z}_r^{\sim k}\hat{\boldsymbol{\lambda}}_a^{\sim k} + \hat{\lambda}_a^k)]/[1+\exp(\mathbf{Z}_r^{\sim k}\hat{\boldsymbol{\lambda}}_a^{\sim k} + \hat{\lambda}_a^k)] - [\exp(\mathbf{Z}_r^{\sim k}\hat{\boldsymbol{\lambda}}_a^{\sim k})]/[1+\exp(\mathbf{Z}_r^{\sim k}\hat{\boldsymbol{\lambda}}_a^{\sim k})]$, in which $\hat{\boldsymbol{\lambda}}_a^{\sim k}$ is a 12×1 vector of parameter estimates except the kth one, and $\hat{\lambda}_a^k$ is the parameter estimate for the kth variable. The effect of the kth variable on the probability that respondent r thinks farmer m could use such forecasts to be more successful is $\hat{P}_{S_{m,r}}^k - \hat{P}_{S_{m,r}}^{\sim k} = [\exp(\mathbf{Z}_r^{\sim k}\hat{\boldsymbol{\lambda}}_m^{\sim k} + \hat{\lambda}_m^k)]/[1+\exp(\mathbf{Z}_r^{\sim k}\hat{\boldsymbol{\lambda}}_m^{\sim k} + \hat{\lambda}_m^k)] - [\exp(\mathbf{Z}_r^{\sim k}\hat{\boldsymbol{\lambda}}_m^{\sim k})]/[1+\exp(\mathbf{Z}_r^{\sim k}\hat{\boldsymbol{\lambda}}_m^{\sim k})]$, in which $\hat{\boldsymbol{\lambda}}_m^{\sim k}$ is a 12×1 vector of parameter estimates except for the kth one, and $\hat{\lambda}_m^k$ is the parameter estimate for the kth variable. The mean effects in the sample are $\bar{\hat{P}}_{S_m}^k - \bar{\hat{P}}_{S_m}^{\sim k}$ and $\bar{\hat{P}}_{I_a}^k - \bar{\hat{P}}_{I_a}^{\sim k}$.

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