Appendix A. An Economic Model of Risk and Palatability in Doneness Choice

To develop the model of behavior estimated for this study, we assumed that consumers maximize utility by choosing hamburger doneness, where health contributes positively to utility, but palatability (taste, tenderness, and juiciness) also contributes to utility. The perceived relationship between palatability and doneness may be bell-shaped for many consumers, with palatability rising to a maximum somewhere between rare and well-done, and then declining past that point. Consumer *i* chooses doneness (*T* for internal temperature) to maximize utility as a function of the palatability of the hamburger (*P*) and the probability of getting sick from the hamburger (*S*). We assume that this decision is separable from other arguments of the utility function, that is, other goods the consumer consumes.

The consumer's problem is:

$$\max_{T} E[U] = E[U(1 - S(T; I)), P(T)] \quad \text{(A1)}$$

where

$E[U]$ = consumer *i*'s expected utility;

T = the internal temperature of the hamburger, an indicator of doneness;

I = information;

$S(T; I)$ = the perceived probability of sickness as a function of the hamburger's doneness, given information I; and

$P(T)$ = the perceived palatability of the hamburger at doneness level T.

The utility-maximizing choice, then, trades off between palatability and the risk of illness so that

$$(\delta E[U] / \delta P)(\delta P / \delta T) = (\delta E[U] / \delta S)(\delta S / \delta T) \quad \text{(A2)}$$

That is, the utility lost from a marginal decrease in palatability is offset by the utility gained from the marginal decrease in the probability of getting sick. The terms $\delta E[U] / \delta P$ and $\delta E[U] / \delta S$ can be interpreted as the importance of palatability and illness probability, respectively, while the derivatives of palatability and illness probability with respect to doneness describe the consumer's perceptions about the relationships between palatability and doneness and the probability of illness and doneness. The model predicts that consumers with higher perceptions of the risk of illness and/or those who attach greater importance to the risk of illness, will be more likely to cook hamburgers thoroughly, given their preferences for a given level of doneness. Similarly, the model predicts that consumers who perceive a less well-done hamburger as more palatable and/or those who consider palatability more important, will be more likely to cook hamburgers less thoroughly.

Note that the model does not account for the decision to stop eating hamburgers because of fear of foodborne illness. Thus, the model reflects only individuals who currently consume hamburgers. Further research is needed to explore the role of risk perceptions and doneness preferences in the decision not to eat hamburgers.

Appendix B. Estimation of the Model of Usual Doneness

We estimated knowledge as a Probit model and estimated the risk motivation index and palatability motivation index using Ordinary Least Squares (OLS). The original survey questions for risk perception, risk importance, rankings of taste, tenderness, juiciness, and the importance of these attributes were answered in ordered categories; equations explaining those variables would have been more appropriately estimated using a limited dependent variable technique. But the index variables were created as products and averages of more than one category, resulting in distributions that were closer to continuous. Thus OLS estimation was acceptable.

If the errors of L_h, L_o, *R, P*, and *K* are uncorrelated, they form a triangular system since risk motivation and food safety knowledge are not modeled as a function of cooking and ordering behavior. However, if the errors are correlated then the knowledge, risk and palatability variables are correlated with the error terms of the cooking and ordering equations, and the unadjusted Probit estimates of these equations will be biased. Further, the estimates of all the equations will be inefficient.

To test the correlation of errors across equations, we used the test suggested by Greene (1993): the sum of squared correlation coefficients for all errors in the system is asymptotically distributed as chi-squared with M(M-1)/2 degrees of freedom, where M is the number of equations in the system (in our case, df=3). We tested for correlation of errors in the following systems:

1) all five equations together,
2) two subsystems consisting of *R, P, K*, and either L_h or L_o,
3) just L_h and L_o together.

Errors across the equations of the five-equation system were significantly correlated. Errors were significantly correlated in the subsystem consisting of L_o, *R, P,* and *K*, but not in the system consisting of L_h, *R, P*, and *K*. Errors for equations for ordering and cooking hamburgers lightly, L_h and L_o, were significantly correlated.

The ideal solution to this problem is a simultaneous nonlinear equations technique (such as Newey, 1987). However, the simultaneous equations estimator may also be biased if the available instrumental variables are poor predictors of the endogenous variables (for the linear case, see Bound et al., 1995). The R-squared values for the risk motivation index and palatability motivation index equations were 0.10 and 0.03, respectively. The pseudo R-squared value for the Probit knowledge prediction equation was 0.06. These values suggest poor predictive power.[1]

Given the low predictive power of the equations for knowledge, the risk index, and the palatability index, results using predictions for these variables are likely to be difficult to interpret. Thus, we applied the Davidson and MacKinnon (1993) test for the significance of the difference between the unadjusted Probit estimates and the estimates from a simultaneous equations technique. In our case, this test is the likelihood ratio test of the significance of the residuals of the knowledge, risk motivation index, and palatability motivation index equations in the cooking and ordering equations. The chi-squared values were 3.57 (p = 0.68, 3 degrees of freedom) for the ordering equation, and 2.18 (p = 0.46, 3 degrees of freedom) for the cooking equation, indicating that estimation using predicted values for knowledge, the risk motivation index, and the palatability motivation index would not be significantly different than the unadjusted equations.

Thus, we estimated the equations for L_h and L_o together as a bivariate Probit model but estimated the equations for knowledge, the risk motivation index, and the palatability motivation index separately.

We multiplied the coefficients of the risk motivation index and the palatability motivation index by multiplying 1.6 and 2 respectively to convert the effects of 1-unit increases to effects of 10-percent increases. A 1-unit increase in the risk motivation index represents 6.25 percent of the maximum scale value of 16, so multiplying the coefficient by 1.6 gives the effects of a

[1] Bound et. al. (1995) shows that for the linear case, the bias in the instrumental variables estimates of the second stage equation is approximated by 1/F times the bias of the OLS estimates, where F is the F-statistic for the prediction equation. Since this system is not linear, the bias cannot be estimated using this approximation.

10-percent increase. Similarly, a 1-unit increase in the palatability motivation index represents 5 percent of the maximum scale value of 20, so multiplying the coefficient by 2 gives the effect of a 10-percent increase.

We also multiplied the coefficient on per capita income in each equation by 5 to convert the effect of a $1,000 increase to the effect of a $5,000 increase.

As in the models for hamburgers recorded in the diary, we estimated the marginal effects of each factor on the dependent variable in absolute and percentage terms. For the bivariate Probit model, however, LIMDEP does not report the marginal effects on the unconditional probabilities. Thus, we estimated the marginal effects by calculating the probability with and without a one-unit change in the independent variable. In the case of dummy variables, we calculated effect as the probability calculated using 1 for the dummy variable minus the probability calculated using 0 for the dummy variable. Again we divided the absolute marginal effect by the sample's average probability to obtain the effects in percentage terms.