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By: **O. Ashton Morgan**, **John C. Whitehead**, William L. Huth, Greg S. Martin, and Richard Sjolander

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ABSTRACT. *We exploit the timing of the BP* Deepwater Horizon *oil spill to develop a unique dataset of oyster consumer actual and anticipated behavior immediately prior to and following the event. A revealed and stated preference model allows both short- and longer-term responses to the spill to be investigated. Findings indicate that the BP spill had a negative impact on oyster demand in terms of short-run actual behavior, although spill effects show signs of dissipating several months following the spill. By accounting for unobserved heterogeneity in the sample, findings further indicate that short- and longer-term spill responses differ across consumer groups.* (JEL Q22, Q51)

I. INTRODUCTION

On April 20, 2010, there was an explosion and fire on the BP-licensed drilling rig *Deepwater Horizon* in the Gulf of Mexico. While the *Deepwater Horizon* rig sunk two days later, the seafloor oil gusher that resulted from the explosion continued to leak until the wellhead was finally capped on July 15, 2010. The *Deepwater Horizon* spill was 20 times the size of the *Exxon Valdez* spill and sent approximately 4.9 million barrels of crude oil into the Gulf of Mexico over a 3 month period. The spill had a negative impact on the Gulf of Mexico fishery. Following the spill, the National Oceanic and Atmospheric Administration (NOAA) closed recreational and commercial fishing in affected federal waters between the mouth of the Mississippi River and Pensacola Bay, Florida. This closure initially incorporated 6,814 mi^2 (17,650 km^2) of Gulf waters. By late June, NOAA had increased the area under closure over a dozen times. At its peak, 88,522 mi^2, or 37% of federal waters, was closed to recreational and commercial fishing in the Gulf.[1]

Due to concerns over potential health risks associated with consumption of contaminated seafood, the federal government also declared a fisheries disaster for Louisiana, Alabama, and Mississippi. Producing almost two-thirds of all oysters consumed in the United States, oysters harvested from the Gulf of Mexico (eastern oysters) are an economically important commercial fish species for both producers and consumers. For producers, between 2001 and 2010, annual landings of Gulf oysters ranged from 16 million to 27 million pounds. Ex-vessel revenue ranged from \$61 million to \$75 million (2010 dollars), accounting for about 10% of total ex-vessel revenue generated by Gulf of Mexico fisheries.[2]

With the flow of oil breaching oyster beds, there were serious concerns that the oil could get into the food chain; a concern that was exacerbated by the use of chemical dispersants that were applied to accelerate the dispersal process. Specifically, the use of disper-

[1] Details of the spill impacts can be retrieved from www.noaanews.noaa.gov/stories2011/20110419_gulf reopening.html.

[2] These data were retrieved from NOAA Fisheries, Fisheries Statistics Division (www.st.nmfs.noaa.gov/commercial-fisheries/index).

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sants can break up the oil into droplets small enough to enter the food chain. Testing found traces of polycyclic aromatic hydrocarbons (PAHs) that are directly linked to oil spills and contain carcinogens in Louisiana coastal waters. PAHs can have serious negative human health effects if they enter the food chain (typically through plankton, finfish, or shellfish), and tests found that levels were 40 times higher than before the spill.[3] Posing an additional potential health risk, researchers also believe that the growth of *Vibrio vulnificus* bacteria can be spurred by oil and contaminants from the spill.[4] *V. vulnificus* is a gram-negative bacterium found naturally in coastal waters along the Gulf, Atlantic, and Pacific coasts, although it is most widespread in the warm waters of the Gulf of Mexico. Along with *V. cholera, V. vulnificus* is considered to be more lethal than the remainder of the vibrios, inhabiting brackish and saltwater, and is found in higher concentrations in summer months when coastal waters are warm.[5] Each year in the United States, approximately 100 individuals become seriously ill (typically by contracting primary septicemia or gastroenteritis) from consuming raw Gulf of Mexico oysters, of which about 35% die from the infection (Scallan et al. 2011). Combined, the direct risk impacts from PAHs entering the food chain and indirect effects on *V. vulnificus* growth may heighten risk perceptions and influence consumer demand for oysters, as a result of the spill. Following the spill, all Louisiana oyster harvest areas were closed. Over the course of the year following the spill, sections of the fishing closures were incrementally lifted on several occasions. Exactly one year to the day of the spill, NOAA reopened the final 1,041 mi^2 of Gulf waters immediately surrounding the *Deepwater Horizon* wellhead.

In general, studies analyzing the effects of contamination incidents or harvesting bans on consumer behavior consistently illustrate that, not surprisingly, news of the incident raises risk perceptions and reduces consumer demand for the product, at least in the short term (Swartz and Strand 1981; Smith, van Ravenswaay, and Thompson 1988; Brown and Schrader 1990; Wessells, Millers, and Brooks 1995). These studies use either market-based data or stated preference methods. Using market data, Swartz and Strand (1981) and Smith, van Ravenswaay, and Thompson (1988) find the postcontamination decline in demand to be short-lived, with the strongest decreases in consumption in the month following the incident, but with consumption returning to its previous level 2 months after the event. The principle constraint of using market data is that examining the effect that news of the event has on consumer behavior requires researchers to create a scaled information variable as a proxy for the provision of media information. The information variable is created in an attempt to account for the total effect of the contamination or harvesting ban incident. However, to what degree these researcher-created variables accurately capture the information effect is debatable. To provide some examples, Wessells, Millers, and Brooks (1995) analyze the effects that news of toxic algae contamination has on mussel demand in Montreal by including a scaled media information variable equal to the weekly number of negative articles appearing in a local newspaper. Swartz and Strand (1981) analyze how news of oyster bed closures in the James River in Virginia due to kepone contamination impact oyster consumer behavior in the Baltimore area. They include an information vector based on the level of newspaper coverage and the likelihood that it negatively influences oyster consumption. Smith, van Ravenswaay, and Thompson (1988) also use an information dummy in their model of sales losses following a milk ban in Hawaii, although they acknowledge potential issues, suggesting that the dummy "is a crude proxy" to capture the information effects, and "it may be more useful to consider more accurate ways of representing diffusion of information about a contamination incident" (p. 13).

Revealed and stated preference (RP/SP) methods can avoid the problem of capturing

[3] Ex-vessel revenue is the quantity of oysters harvested by commercial oyster farmers, multiplied by the average price received by them at the first point of sale.

[4] See www.reuters.com/article/2010/09/30/us-oil-spill-carcinogens-idUSTRE68T6FS20100930.

[5] See www.foodsafetynews.com/2010/07/will-oil-eating-bacteria-plague-the-gulf/.

the media information effect by disseminating specific risk information across respondents. The effects of the information treatment on expected consumer behavior can then be isolated.[6] Parsons et al. (2006), Morgan, Martin, and Huth (2009), and Morgan et al. (2013) survey consumers and use RP/SP methods to examine the effects of consumer health-risk information on seafood consumer behavior. They provide respondents with hypothetical health-risk information based on actual media coverage and examine their behavioral responses. Results from these studies all suggest that consumption risk information raises risk perceptions and causes a decrease in demand. In a study that specifically considers oil spill impacts, Wessells and Anderson (1995) survey 156 Rhode Island households to examine factors affecting seafood consumption behavior and seafood safety perceptions. Using a recursive system of equations that describes the influence of seafood safety perceptions on expected demand, they find that consumers anticipate a decrease in seafood consumption if faced with hypothetical negative information regarding an oil spill and closure of the Naragansett Bay to fishing. However, while stated preference methods provide a means to directly measure the impact of contamination information on behavior, a common drawback is that these analyses are typically confined to examining short-term and arguably heightened consumer reactions to an event, as consumers' consumption changes are elicited immediately following exposure to an information treatment. In this research, due to the timing of the spill, we develop a pre- and postspill RP/SP framework that models individuals' actual and expected oyster consumption behavior over the spill period. The unique dataset and modeling approach enables the impact of the spill on oyster consumers' risk perceptions and, in turn, consumption behavior, to be analyzed in both the short and longer terms. We provide a timely contribution to the body of literature examining the impacts of contamination events on consumer behavior, especially after an event of the magnitude of the BP spill. Specifically, we survey oyster consumers on their actual and expected oyster consumption choices in March and April 2010, collecting the last observation on the morning of the *Deepwater Horizon* explosion. We then resample a portion of these respondents after the spill to again elicit actual and anticipated consumption behavior. A pre- and postspill RP/SP model framework is developed to measure oyster consumers' responses to a major spill event, and associated changes in individual and aggregate welfare. Our findings extend any previous research in this area that we are aware of by taking advantage of the timing of the spill to examine the impacts of the spill on both short-term actual consumption behavior and longer-term anticipated behavior. As such, we focus solely on demand-side impacts resulting from the spill and do not consider any changes to producer surplus. Results from pre- and postspill RP/SP measures show that, as expected, the spill has a negative impact on short-term actual demand by the average respondent. This creates aggregate welfare losses in the region of $4 million. However, the negative spill effects dissipate over the longer-term horizon as anticipated consumption begins to return toward prespill levels. We also consider the impact of the remaining oyster harvesting ban length on behavior. We find that the longer the period between respondents' expectations regarding the length of the ban and its actual duration, the greater the reduction in oyster consumption.

To provide a deeper analysis into consumers' behavioral responses, we also incorporate unobserved heterogeneity into the RP/SP framework by estimating a latent class model. The latent class model investigates whether actual and expected behavior of different classes of consumer varies due to the spill.

II. SURVEY, SAMPLING, AND STUDY DESIGN

We developed an Internet-based survey of oyster consumers (aged 18 and over), sampled from the U.S. Centers for Disease Control–

[6] Higher temperature-based concentrations of *V. vulnificus* between May and August is one reason for the common adage among raw oyster consumers to "eat oysters only during the 'R' months."

designated "case states."[7] These are Florida, Alabama, Mississippi, Louisiana, Texas, and California.[8] The online survey was administered by Online Survey Solutions, Inc. (OSS), and the survey was administered between March and April 2010. The last observation for Survey 1 was collected on April 20, 2010, the day of the BP *Deepwater Horizon* explosion, but before any public announcement regarding a spill was made. The purpose of the first survey is to gather data on oyster consumers' attitudes, preferences, awareness and perceptions of oyster consumption health risk, knowledge about oyster consumption health risk. and relevant demographic data. Also, to meet our initial research objectives, respondents were asked a series of stated preference questions. These questions were designed to elicit consumption behavior under existing conditions and after being provided with different educational information treatments and information on postharvest processing methods. Usable observations from 1,849 oyster consumers were collected.[9] We now refer to this survey as the prespill survey.

By survey design, respondents from the prespill survey were first asked about their current annual consumption frequency to generate pretreatment baseline data for oyster consumption experience (revealed preference). To aid the respondents in determining the annual amount, they were asked how many months in a year they typically consumed an oyster meal, and then, in a typical month in which they ate oyster meals, about how many oyster meals they ate.[10] The survey software then computed the annual number of meals, and respondents were offered the opportunity to adjust the number if desired. Responses to this question represent the prespill revealed preference annual number of oyster meals consumed (*RP1*). Next, respondents were asked whether, compared to the number of meals they revealed they consumed in a typical year, they expected to eat more, less, or the same number of oyster meals in the next year. Respondents were then prompted to state how many more or less as required (stated preference). In estimation, inclusion of a stated preference count under existing conditions provides a means to control for potential hypothetical bias in individual responses (Whitehead et al. 2008). Responses represent a prespill stated preference meal count (SP1). Finally, in order to derive an oyster demand curve, respondents were also asked to state whether they would eat more, less, or the same number of meals under both a price increase and a price decrease scenario (while being informed that the price of all other food products remained the same), where the price changes were varied randomly across respondents. Each respondent received a price increase of \$1, \$3, \$5, or \$7, or a price decrease of \$1, \$2, \$3, or \$4.

With the timing of the prespill survey and the BP spill, we developed a follow-up survey designed to elicit individuals' attitudes regarding the spill, seafood safety concerns, expectations regarding the length of the oyster harvest ban in Louisiana, and stated preference consumption based on expected ban length. We refer to this as the postspill survey. The online postspill survey was again administered by OSS in November/December 2010 (7 to 8 months following the spill). As part of this effort, we resampled some of the respondents from the prespill Survey 1. In total, the postspill survey collected 1,087 observations, of which, 504 respondents had also answered

[7] Both RP data and SP data have their individual strengths and weaknesses. The major drawback of the RP method is that analyzing changes in behavior may not be feasible because individuals may not be able to form preferences due to lack of an actual experience. The major strength of RP data is that it is based on actual behavior (although this may be constrained by individuals' ability to accurately recall past behavior). SP methods are constrained by their hypothetical approach but benefit from their flexibility. Overall, the strengths of both approaches can be exploited through joint estimation of RP and SP data. Essentially, joint estimation has the advantage of allowing the measurement of preferences outside of an individual's historical experience while anchoring the stated preference responses to actual behavior (Rosenberg and Loomis 1999; Grijalva et al. 2002; Whitehead 2005; Egan and Herriges 2006).

[8] U.S. Centers for Disease Control case states are states in which there are documented cases of *V. vulnificus*–related deaths.

[9] Due to a request from Georgia Sea Grant, we also sampled consumers from that state.

[10] A more in-depth discussion of the prespill survey is detailed by Morgan et al. (2013).

the prespill survey. In total, there were 382 usable responses from oyster consumers that completed all the prespill and postspill RP/SP elements from both surveys.[11]

In the postspill survey, we asked respondents the same four RP/SP questions as described in Survey 1. Again we asked respondents about their actual and expected annual oyster meals consumed (which we refer to as RP2 and SP2, respectively) plus stated preference price increase and decrease scenarios. Combined, the pre- and postspill RP/SP questions enable an investigation into the short- and longer-term effects of the spill on oyster consumer behavior.[12] It should be highlighted that there is an overlap between pre- and postspill periods. For example, as the postspill survey was administered approximately 8 months after the spill, RP2 data overlap with SP1 data for a period of 4 months. This likely impacts coefficient estimates. To examine this, Whitehead, Morgan and Huth (2013) analyze the predictive validity of the before/after data and controlling for the overlap in pre- and postspill time periods. They find that there are small forecast improvements in revealed preference oyster meals using the stated preference oyster meals relative to the revealed preference oyster meals from the first survey.

In addition, following the spill, a ban on harvesting oysters from Louisiana oyster beds was mandated. At the time of the postspill survey, the ban remained in place for approximately 50% of Louisiana oyster beds. We were interested in examining, not only how a partial ban on oyster harvesting impacted consumer behavior, but to investigate how the length of the existing ban relative to individuals' expectations impacted consumption behavior. To accomplish this, we asked a further SP question under an oyster harvesting ban scenario. Under this scenario respondents were informed that the State of Louisiana Health and Hospitals "closed" several Louisiana shellfish harvest areas to the harvest of oysters and other molluscan shellfish. While some shellfish harvest areas had since reopened, the ban on oyster harvesting from many of Louisiana's shellfish harvest areas remained in place. Respondents were then asked how long they expected the ban to last, from a list of seven possible durations (1 = Not much longer; 2 = About a month; 3 = About 3 months; 4 = About 6 months; 5 = About 9 months; 6 = About a year; and 7 = More than a year). Next, respondents were told to imagine that the Louisiana ban on harvesting oysters from affected areas would last for about another [number], where [number] was randomly assigned and varied across respondents from a list of four possible values, namely, "month," "3 months," "6 months," or "9 months." Respondents were then asked: "Suppose that the average price of your oyster meals stays the same, compared to the number of oyster meals you previously told us you expect to eat next year. Do you think you will eat more, less, or about the same number of oyster meals next year?" Again, respondents were prompted to state how many more or less, as required.

Table 1 defines all pre- and postspill RP/SP scenarios and provides descriptive statistics for meal counts elicited under each scenario plus under each expected ban length treatment. Table 2 provides sample definitions and descriptive statistics for variables used in the analysis for the sample. The majority of respondents were female (53%) and Caucasian (79%) with an average sample age of 47 years and earning an average household income of $73,500. Less than half of respondents believed that Gulf oysters were safe to eat following the spill. Approximately 68% of respondents consumed raw oysters and 17% were immune-compromised, as they indicated that they have one of the health conditions necessary to be vulnerable to a *V. vulnificus* infection (e.g., diabetes, liver disease, iron overload disease, stomach disorders, and HIV).

[11] Respondents were informed that oyster meals included any meal in which the main course was oysters, or oysters were an important ingredient in the dish (like gumbo), or meals in which there was an oyster appetizer. Pictures were also displayed to provide examples of oyster meals.

[12] It is worthwhile noting, therefore, that in our RP/SP design, we focus on current and past oyster consumers, and not potential consumers.

TABLE 1

Pre- and Postspill Revealed and Stated Preference (RP/SP), and Ban Length Scenario Meal Count Statistics

SP Scenario	Description	Mean Meal Count	Std. Dev.
Prespill Survey			
RP1	Observed annual number of oyster meals consumed	21.9	45.8
SP1	Expected annual number of oyster meals consumed	22.3	46.4
SP1 Price Increase	Expected annual number of oyster meals consumed with price increase	18.6	41.6
SP1 Price Decrease	Expected annual number of oyster meals consumed with price decrease	25.1	49.1
Postspill Survey			
RP2	Observed annual number of oyster meals consumed	17.5	38.9
SP2	Expected annual number of oyster meals consumed	18.3	42.3
SP2 Price Increase	Expected annual number of oyster meals consumed with price increase	16.7	43.3
SP2 Price Decrease	Expected annual number of oyster meals consumed with price decrease	20.6	44.4
SP2 Ban	Expected annual number of oyster meals consumed with 1, 3, 6, or 9 month ban	18.3	43.1
Ban Length			
1 month	Expected annual number of oyster meals consumed if spill lasts for about 1 more month	15.7	36.2
3 months	Expected annual number of oyster meals consumed if spill lasts for about 3 more months	19.1	42.9
6 months	Expected annual number of oyster meals consumed if spill lasts for about 6 more months	22.2	51.9
9 months	Expected annual number of oyster meals consumed if spill lasts for about 9 more months	16.3	41.4

TABLE 2

Descriptive Statistics

Variable	Description	Mean	Std. Dev.	Min.	Max.
PRICE	Change in price of oyster meals	1.02	2.24	− 5.00	6.00
QUANTITY	Average annual oyster meals consumed	19.92	43.99	0.00	380.00
AGE	Age of respondent	47.46	17.76	18.00	89.00
GENDER	Respondent is male (= 1)	0.47	0.50	0.00	1.00
RACE	Respondent is Caucasian (= 1)	0.79	0.41	0.00	1.00
INC	Household income of respondent (thousands of dollars)	73.51	38.39	8.00	150.00
RP1	Revealed preference question from the prespill survey (= 1)	0.11	0.31	0.00	1.00
RP2	Revealed preference question from the postspill survey 1 (= 1)	0.11	0.31	0.00	1.00
SP1	Stated preference question from the prespill survey (= 1)	0.33	0.47	0.00	1.00
SP2	Stated preference question from the postspill survey 1 (= 1)	0.44	0.50	0.00	1.00
RAW	Consumes raw oysters (= 1)	0.68	0.47	0.00	1.00
BAN_LENGTH	How much longer respondents expect ban to last (1 = Not much longer; 2 = About a month; 3 = About 3 months; 4 = About 6 months; 5 = About 9 months; 6 = About a year; 7 = More than a year)	4.86	2.05	1.00	7.00
BAN	Stated remaining length of Louisiana harvesting ban (1 = About a month; 2 = About 3 months; 3 = About 6 months; 4 = About 9 months)	2.41	1.16	1.00	4.00
BAN_DIFF	Difference between BAN_LENGTH and BAN	1.45	2.42	− 4.00	5.00
AT-RISK	Consumer is vulnerable to *V. vulnificus* infection (= 1)	0.17	0.38	0.00	1.00

III. THE CONCEPTUAL FRAMEWORK

Both pre- and postspill RP/SP data for a model of oyster consumer consumption behavior were collected via an online survey instrument. Pre- and postspill RP data were based on the actual annual number of oyster meals consumed. Pre- and postspill SP data were used to stimulate an expected change in oyster meals consumed resulting from price changes and a ban on Louisiana oyster harvesting due to the BP spill. Specifically, SP questions were asked about future meals consumed: (1) under prespill existing conditions, (2) with a prespill price increase and decrease scenario, (3) under postspill existing conditions, (4) with a postspill price increase and decrease scenario, and (5) with a postspill ban on Louisiana oyster harvesting continuing for another month to 9 months.

One issue that needed to be addressed was that in the prespill survey framework, respondents' baseline meal prices were not elicited. This was because previous research had shown that it makes little difference in estimation whether the full meal price or a randomly assigned change in price is used as an independent variable in RP/SP demand models (Parsons et al. 2006; Haab et al. 2010). Unfortunately, this therefore meant that we were not able to estimate a change in oyster meal price as a result of the spill. The lack of an adequate measure of how the spill impacted meal prices would therefore constrain any meaningful welfare analyses involving pre- and postspill data. To address this, we separately estimated a change in oyster meal prices due to the spill and imputed the after-spill price change into the model. To do this, the change in postspill price was analyzed by obtaining baseline price data before and after the spill from the National Marine Fisheries Service. A model of Eastern oyster ex-vessel prices was then developed:

$$xp = \alpha + \beta Q + \gamma \mathbf{S} + \delta M + \phi Y + \theta BP, \tag{1}$$

where xp is the ex-vessel price per pound, Q is pounds landed, **S** is a vector of dummy variables for the state, M is the month, Y is the year, and BP is a dummy variable equal to 1 during months when the oil spill affected the oyster harvest (we use May–December 2010). Results from a random effects panel model on ex-vessel prices indicated that the BP oil spill caused a supply shock that increased oyster prices in 2010, but prices then fell back to prespill levels in 2011. Assuming that the price of an Eastern oyster meal in a state is proportional to the ex-vessel price, and adjusting for various markup factors, we estimated that the mean increase in oyster meals due to the BP oil spill was approximately \$2 per meal.[13]

As the dependent variable, actual and expected meal counts is a nonnegative integer with a high frequency of low meals consumed, a count panel data model is estimated:

$$\Pr(x_{it}) = \frac{e^{-\lambda_{it}}\lambda_{it}^{x_{it}}}{x_{it}!}, x_{it} = 0, 1, 2, \ldots. \tag{2}$$

The natural log of the mean number of meals is assumed to be a linear function of prices, sociodemographic indicators, consumption behavior and health characteristics, and a ban scenario scaled variable. To allow for variation across oyster consumers that cannot be explained by the independent variables, we assume that the mean number of meals also depends on a random error, u_i. The RP/SP Poisson demand model is

$$\begin{aligned} \ln\lambda_{it} = {} & \beta_0 + \beta_1 P_i + \beta_2 y_i + \beta_3 \mathbf{s} + \beta_4 \mathbf{c}_i + \beta_5 RP2 \\ & + \beta_6 SP1 + \beta_7 SP2 + \beta_8 BAN\_DIFF + \mu_i, \end{aligned} \tag{3}$$

where P is the change in price of an oyster meal; y is income; **s** is a vector of sociodemographic variables; **c** is a vector of individual consumption and health characteristics; individuals are indexed $i = 1, \ldots, 382$; and $t = 1, \ldots, 9$ denotes annual oyster meal demand under a prespill RP status quo treatment, postspill RP status quo, prespill SP status quo, postspill SP status quo, prespill SP price increase, prespill SP price decrease, postspill SP price increase, postspill SP price decrease, and a postspill SP information treatment on a Louisiana oyster harvesting ban in the pseudo-panel data. The scaled dummy

[13] Full details of the ex-vessel price model are available upon request.

variable *BAN_DIFF* (*BAN_DIFF* = 1 when $t = 9$) captures the temporal difference between respondents' expected ban horizon and the actual ban horizon (the duration of which they are informed of in the ban treatment). $SP = 1$ for hypothetical meal data ($t = 3, \ldots, 9$) and 0 for revealed meal data ($t = 1$ and 2). β_0 through β_8 are coefficients to be estimated in the model. Pooling the data suggests that panel data methods be used to account for differences in variance across sample individuals, i, and scenarios, t. The distribution of meals conditioned on u_i is Poisson with conditional mean and variance, λ_{it}. If $\exp(\lambda_{it})$ is assumed to follow a gamma distribution, then the unconditional meals, x_{it}, follow a negative binomial distribution (Hausman, Hall, and Griliches 1984). The random effects Poisson model imposes positive correlation across the t scenarios (Landry and Liu 2011).

With the semilog functional form, the baseline economic benefit per annual oyster meals consumed for the representative consumer as measured by average annual per-person consumer surplus (CS) is

$$CS = \frac{\hat{x}}{-(\beta_1)}, \qquad [4]$$

where $\hat{x}$ is the annual number of predicted meals for the representative oyster consumer and all independent variables are set at sample means (Bockstael and Strand 1987). The short-run change in annual per-person consumer surplus as a result of the spill is represented by

$$CS = \frac{(\hat{x}) - (x')}{-(\beta_1)}, \qquad [5]$$

where $\hat{x}$ and x', represent pre- and postspill actual meal counts. The long-run consumer surplus effects due to the spill are estimated in a similar fashion with the appropriate RP/SP meal counts.

There is a developing body of literature in economics that examines preference heterogeneity in individuals' behavior. We follow these studies by developing a finite mixture, or latent class model, that allows behavioral responses to the health-risk information treatments to be examined across classes of consumer. We then compare results from the standard pooled RP/SP model to the latent class model findings. Formally, the latent class model is described by an individual consumer who resides in a latent class, c. The individual class membership (denoted by $C_i^* = 1, \ldots, n$) is unknown (latent) to the researcher. The underlying utility of individual i's consumption x, under information treatment t, given that the individual belongs to latent class c, can be expressed as

$$U_{ixt} = \boldsymbol{\beta}_c' \mathbf{X}_{ixt} + \varepsilon_{ixt}, \qquad [6]$$

where ε_{ixt} is an independent identically distributed (i.i.d) error term (from the analyst's perspective) and indicates the unobserved heterogeneity for individual i's consumption x, under information treatment t, and $\boldsymbol{\beta}_c'$ is a class-specific vector of parameters to be estimated from the observed attribute vector, $\mathbf{X}_{ixt}$.

For each class, the actual number of annual meals consumed, x_i, is assumed to be drawn from a Poisson distribution. Within each class, the underlying parameters of the Poisson distribution are allowed to vary. Specifically, we assume that

$$\Pr(y_i^* = m \mid C_i^* = c) = \frac{\exp(-\lambda_{ic})\lambda_{ic}^m}{m!}$$
$$i = 1, \ldots, I{:}\, c = 1, \ldots, n, \qquad [7]$$

where $\lambda_{ic} = \exp(\mathbf{X}_i' \boldsymbol{\beta}_c)$ represents the conditional mean number of oyster meals consumed in class c given characteristics $\mathbf{X}_i$ and the parameter vector $\boldsymbol{\beta}_c$.

IV. RESULTS

Table 3 presents the results from a random effects Poisson model and a four-class latent class model. The dependent variable in all models is the annual number of oyster meals consumed. The model in the first column is the random effects Poisson model that assumes a homogenous mean influence of the spill and other explanatory variables on annual oyster meal demand. Columns (2) through (5) present the findings from a panel

TABLE 3
Random Effects Poisson RP/SP Model and Latent Class Model

Variable	Random Effects Poisson Model	Latent Class Model			
		Latent Class 1	Latent Class 2	Latent Class 3	Latent Class 4
CONSTANT	2.764***	4.268***	2.531***	1.052***	1.510***
	(0.239)	(0.027)	(0.031)	(0.074)	(0.044)
PRICE	− 0.052***	− 0.033***	− 0.061***	− 0.075***	− 0.054***
	(0.001)	(0.003)	(0.003)	(0.007)	(0.003)
INC	− 0.002**	− 0.005***	− 0.001***	− 0.001***	0.005***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
MALE	0.388***	0.320***	0.232***	0.384***	0.181***
	(0.091)	(0.008)	(0.008)	(0.011)	(0.006)
AGE	− 0.003	− 0.026***	0.005***	0.000	0.020***
	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)
RP2	− 0.118***	0.221***	− 0.668***	0.051	0.763***
	(0.009)	(0.033)	(0.054)	(0.103)	(0.052)
SP1	− 0.020**	− 0.024	− 0.026	− 0.042	0.003
	(0.009)	(0.033)	(0.036)	(0.094)	(0.058)
SP2	− 0.065***	0.186***	− 0.730***	0.053	0.781***
	(0.007)	(0.023)	(0.027)	(0.072)	(0.044)
RAW	0.645***	0.710***	0.238***	0.325***	0.089***
	(0.110)	(0.010)	(0.008)	(0.012)	(0.009)
AT-RISK	− 0.449***	0.237***	− 0.238***	0.001	− 0.707***
	(0.155)	(0.012)	(0.011)	(0.016)	(0.010)
BAN_DIFF	− 0.022***	− 0.036***	− 0.004	− 0.032**	0.006
	(0.001)	(0.008)	(0.010)	(0.015)	(0.005)
Alpha	1.172	0.967	15.659	5.297	9.782
Sample size	382	382	382	382	382
Periods	9	9	9	9	9
Class probabilities		0.128	0.277	0.454	0.140
AIC	137,446.4	28,216.7			
BIC	137,514.0	28,530.1			
Log-likelihood	− 68,712.2	− 14,057.3			

Note: Standard errors are in parentheses. AIC (Akaike information criterion) = $-2(\text{LLB} - P)$; BIC (Bayesian information criterion) = $[(-2 \times \text{LLB}) + (k \times \ln(n))]$.

** Significance at the 5% level; *** significance at the 1% level.

model that allows for unobserved heterogeneity with respect to actual and expected annual meal counts and other explanatory variables. We refer to this as the latent class model. We estimated a latent class model with 2, 3, 4, and 5 classes and then compared two measures of fit first developed by Hurvich and Tsai (1989). We report the Akaike information criterion (AIC) and Bayesian information criterion (BIC). Scarpa, Thiene, and Tempesta (2007) describe how these statistics help direct the researcher as to the number of classes to choose. As the five-class model failed to converge and the four-class specification had the lowest score on both criteria across the remaining models, we report results from this model only. Also reported in Table 3, the four-class model specification finds that there is a 13% probability that sampled respondents belong to Class 1, 28% to Class 2, 45% to Class 3, and 14% to Class 4.

Per-person, per-meal, and annual per-person consumer surplus measures are presented in Table 4, together with 95% confidence intervals constructed using a bootstrapping procedure (Krinsky and Robb 1986). The procedure generates 10,000 random variables from the distribution of the estimated parameters and generates 10,000 consumer surplus estimates. The estimates are sorted in ascending order, and the 95% confidence intervals are found by dropping the bottom and top 2.5% of the estimates.

For the average consumer in the sample, the price coefficient is, as expected, negative and highly statistically significant, so oyster

TABLE 4

Consumer Surplus (CS) Estimates (in Dollars)

Panel Model			Change in Mean Annual CS			
Specification	Mean CS per Meal	Mean Annual CS	RP2-RP1	RP2-SP1	SP2-SP1	SP2-RP2
Random effects Poisson	19.15 (18.63, 19.72)	427.21 (415.44, 439.62)	−9.39 (− 9.66, − 9.14)	−8.46 (− 8.70, − 8.23)	−6.44 (− 6.63, − 6.26)	2.02 (1.96, 2.07)
LC model						
Class 1	30.32 (23.49, 37.15)	676.21.04 (523.88, 828.54)	17.89 (13.86, 21.92)	23.65 (18.32, 28.98)	68.23 (52.86, 83.60)	N/A
Class 2	16.32 (14.61, 18.01)	363.71 (325.74 401.68)	− 20.39 (− 22.51, − 18.26)	− 17.78 (− 9.64, − 15.92)	− 76.17 (− 84.12, − 68.22)	N/A
Class 3	13.28 (10.96, 15.60)	296.13 (244.31, 347.95)	N/A	N/A	N/A	N/A
Class 4	18.52 (16.24, 20.81)	413.17 (362.25, 464.11)	27.05 (23.72, 30.39)	26.68 (23.39, 29.97)	125.81 (110.30, 141.31)	N/A

Note: 95% confidence intervals are in parentheses. LC, latent class; N/A, not applicable.

consumer behavior conforms to the law of demand. The price coefficient from the standard model implies a per-person, per-meal consumer surplus estimate of \$19.15, or an annual per-person estimate of \$427.[14] Based on our estimate of 467,000 Gulf of Mexico oyster consumers, this equates to approximately \$199 million in aggregate welfare for Gulf of Mexico oyster consumers.[15] Once we account for unobserved heterogeneity in the sample, the price coefficients in the latent class model vary across consumers, indicating variation in consumer welfare across classes. For Class 1, 2, 3, and 4 consumers, per-meal consumer surplus estimates range from \$13.28 to \$30.32.

Parameter estimates for the RP/SP coefficients examine the effect of the spill on short-run actual behavior and longer-term expected behavior. We examine consumers' short-run response to the spill in two ways: by comparing postspill actual meal counts (*RP2*) to both prespill actual (*RP1*) and prespill expected meal counts (*SP1*). First, the coefficient of *RP2* is negative and statistically significant at the 1% confidence level, so the actual number of oyster meals consumed by individuals after the spill is below prespill actual meal counts. It is worth noting that as all counts are annual, this avoids any potential seasonal effects in oyster-consuming behavior, so we attribute any change in actual meals consumed solely to the spill. Also, the coefficient of *RP2* is greater in magnitude than the coefficient of *SP1*, so postspill actual demand also falls below prespill expectations, reaffirming that the

[14] The baseline level for mean annual expected meal counts is 21.9. It should be noted that we consider reduced demand following the spill as a loss in individual welfare, or an avoidance cost, as first posited by Swartz and Strand (1981) in their paper, coincidently also examining the effects of contamination news on oyster demand.

[15] Our estimate of 467,000 Gulf of Mexico oyster consumers is based on average annual landings of 22 million pounds of oysters. With a 100-pound sack containing about 250 oysters and the average oyster meal containing about 6 oysters, this equates to consumers eating about 9.3 million Gulf of Mexico oyster meals annually. Sampled respondents indicate they consume an average of 19.9 meals per year (see Table 2). This implies 467,000 Gulf of Mexico oyster consumers.

spill reduces short-run demand.[16] Combined, these findings indicate that demand from the average consumer declines significantly in the short run following the spill. These measures imply a loss in per-person, per-meal consumer surplus of between \$8.46 and \$9.39, or between \$4.0 and \$4.4 million in aggregate annual welfare.[17]

The latent class model highlights heterogeneity in the data with regard to short-term actual spill responses. While Class 2 consumers behave in line with an average consumer, reducing short-run demand in response to news of the spill, Class 3 consumers are insensitive to spill news, indicating no change in oyster demand. Conversely, both Class 1 and 4 consumers increase oyster consumption once news of the spill is disseminated. Some possible explanations for this behavioral response are that perhaps these consumers do not perceive any negative health effects pertaining to the spill, or that they are more sympathetic to the oyster industry and so are expressing a sense of support for the industry by increasing oyster demand following the event. For the Class 1 group in particular, another possibility is that they may be generally less risk averse than the average consumer. This notion is perhaps supported by the positive and significant coefficient on the *AT-RISK* parameter. Recall, immune-compromised consumers are vulnerable to morbidity and mortality risk from consuming Gulf oysters due to the potential presence of *V. vulnificus* bacteria. While the average at-risk consumer eats fewer oyster meals than a nonvulnerable consumer, vulnerable Class 1 consumers consume more meals, suggesting a degree of risk insensitivity in oyster consumption.

For longer-term impacts associated with the spill, again two comparisons are important. First, we examine whether the number of oyster meals consumers expect to eat after the spill differs statistically from prespill expectations. We compare a restricted model ($SP = SP1 + SP2$) with the standard, unrestricted model that allows pre- and postspill stated preference counts, under existing conditions, to vary. A likelihood ratio test suggests a greater than 95% probability that the two models are significantly different, so for the average consumer, expected meal counts elicited after the spill are significantly different from those elicited before the spill. As the coefficient of *SP2* is greater in absolute terms than the coefficient of *SP1*, the spill also has a long-term impact of reducing expected demand.[18] However, by comparing *RP2* and *SP2* coefficients 8 months after the spill, it appears that the long-term negative responses to the spill are tempered and demand begins to increase with time. That is, we see a rebound in oyster demand as consumers indicate that they anticipate consuming more oyster meals in the future than they did in the few months following the spill.[19] Over time, demand is moving back toward its prespill baseline and welfare losses are mitigated. There may be several causes driving this effect; however, we suspect that the principle factor is that individuals perceive that the negative effects of the spill lessen over time (and water quality conditions improve) and as such expect to increase future consumption. The increase in postspill expected demand relative to actual demand increases per-person, per-meal welfare by \$2.02, and annual aggregate welfare by \$0.9 million.

Again, we observe long-run behavioral differences across subgroups. Once more, Class 3 consumers are nonresponsive to the spill over a longer-term horizon. For Class 2 consumers, *RP2* and *SP2* estimates are not statistically different from zero, so we do not observe any long-term rebound in demand. Instead, the short-term fall in demand persists

[16] We also assume that time-variant factors that we do not control for (such as income) do not impact demand over this period. However, we believe that this is a strong and valid assumption based on the relatively short time frame of the analyzed impacts and the relatively anemic economic conditions at the time.

[17] A Wald test ($W = 0.098$ with probability value = 0.00) indicates that the difference between prespill expected meals and postspill and actual meals (SP1 and RP2) is statistically different from zero.

[18] This can perhaps be viewed as a lower-bound estimate of welfare losses, as the second survey was conducted 8 months following the spill. As such, 4 months of the RP2 counts were consumed prior to the spill.

[19] A Wald test ($W = -0.045$ with probability value = 0.00) indicates that the difference between prespill and postspill expected meals (SP1 and SP2) is statistically different from zero.

over a longer-term horizon with no statistically significant increases in welfare. For Class 1 and 4 consumers, we also do not observe any long-term changes in behavior after the spill, so the positive spill impacts continue into the future.

Finally, at the time of the survey a partial ban on harvesting oysters was in place for Louisiana oyster beds. The final SP question in the postspill survey asked respondents to state any change in expected behavior in response to a randomly assigned continuation of the ban. In estimation we code the ban variable (*BAN_DIFF*) as the difference between individuals' expected length of the ban (*BAN_LENGTH*) and the stated length of the ban (*BAN*). As such, *BAN_DIFF* captures the difference between individuals' expected and actual ban length. The negative and highly significant coefficient on the *BAN_DIFF* variable indicates that the longer the period between respondents' expectations regarding the length of the ban and its actual duration significantly reduces oyster consumption. In the literature, the effect of a harvesting ban is typically captured by examining how consumption behavior changes to news of a ban at a single point in time (Swartz and Strand 1981; Smith, van Ravenswaay, and Thompson 1988; Wessells, Miller, and Brooks 1995). We also ran the model using a simple dummy variable equal to 1 when stated preference counts were elicited under the ban scenario.[20] The ban coefficient was not statistically significant. Combined, these findings provide some additional insight into consumers' reaction to a harvesting ban by illustrating that consumers' responses to a ban can't necessarily be represented by a binary variable (i.e., they are responsive only to a ban or no ban scenario), but rather, that the length of the ban relative to expectations can be influential.

V. CONCLUSIONS

This research takes advantage of a unique dataset of oyster consumer behavior to analyze the impact of the BP *Deepwater Horizon* oil spill on consumer demand. Using a repeat sample of oyster consumer behavior immediately before and approximately 8 months following the spill, we develop an RP/SP model that extends the findings of other research in this area by enabling both the short-term and longer-term impacts of the spill on oyster demand to be analyzed.

Results show that, as expected, the BP spill significantly reduced demand for oysters in the months following the spill. This short-term reaction is in line with several other studies looking at health scare demand effects (Swartz and Strand 1981; Smith, van Ravenswaay, and Thompson 1988; Brown and Schrader 1990; Parsons et al. 2006). However, while studies using market-based data typically demonstrate that decreases in demand return to their baseline level after 1 to 2 months, our results indicate that 8 months after the spill, demand remained below prespill levels, so welfare losses persisted. Further, while studies using stated preference methods constrain demand impacts and welfare measures to one point in time following the event, our pre- and postspill survey framework enables an investigation of the effects of the spill on expected behavior over a longer-term horizon. For the average respondent, 8 months after the spill, the negative spill effects dissipate and we observe demand starting to pick up again, although expected demand still remains below prespill levels.

While the standard RP/SP model assumes a homogenous mean influence of the spill and other explanatory variables across sampled oyster consumers, we also incorporate unobserved heterogeneity into the RP/SP framework by estimating a latent class model. The latent class model provides a deeper analysis into consumers' behavioral responses to the spill by investigating whether the short- and longer-term behavioral impacts vary across classes of consumer. In a four-class latent class model, results show that for one group of consumers, short-term responses to the spill are in line with those of the average consumer. Conversely, two other groups respond to news of the spill by increasing demand. We reconcile this result by suggesting that these groups perhaps exhibits less risk-averse behavior, a notion that is supported by at-risk consumers

[20] A Wald test ($W = 0.05$ with probability value = 0.00) indicates that the difference between postspill actual (RP2) and expected (SP2) meals is statistically different from zero.

TABLE A1

Postspill Price Changes

Variable	Label	Mean	Coeff.	Std. Err.	*t*-Stat.
Intercept			3.035	0.2790	10.88
Pounds	Landings in 1,000s	415	0.00012	0.000099	1.20
October	= 1 if October	0.094	0.335	0.1459	2.30
Alabama	= 1 if Alabama	0.094	0.750	0.5023	1.49
Florida	= 1 if Florida	0.26	− 0.690	0.4953	− 1.39
Year 2009	= 1 if 2009	0.33	0.0367	0.1390	0.26
BP × 2010	= 1 if postspill in 2010	0.21	0.527	0.1517	3.47
Year 2011	= 1 if 2011	0.33	0.0984	0.1394	0.71

Note: Dependent variable = Real oyster ex-vessel price/lb (mean = $3.17). $N = 138$.

in the group consuming more oyster meals. For all three groups, time does not mitigate their response behavior, as their responses continue 8 months after the event. As such, the negative/positive impacts are also felt in the longer term.

APPENDIX: POSTSPILL PRICE ESTIMATION

Our approach to obtaining baseline price data before and after the spill was to develop a model of Eastern oyster ex-vessel prices: $xp = \alpha + \beta Q + \gamma \mathbf{S} + \delta M + \theta BP$; where xp is the ex-vessel price per pound, Q is pounds landed, **S** is a vector of dummy variables for the state, M is the month, Y is the year, and BP is a dummy variable equal to 1 during months when the oil spill affected the oyster harvest (we used May–December 2010). A positive and significant coefficient for θ indicates that the BP oil spill caused a supply shock that increased oyster prices.

Assuming that the price of an Eastern oyster meal in a state is proportional to the ex-vessel price, we added the survey-induced price change to the ex-vessel price (with a wholesale-to-retail markup estimate from the National Marines Fisheries Service) to construct a state-level price variable before and after the oil spill. Ex-vessel price data were adjusted for inflation using the Food and Agriculture Organization's fish (producer) price index for the United States from 2009 to 2011 (Tveterås et al. 2012).

We operationalized the above model with Gulf of Mexico landings data from the National Marine Fisheries Service and estimated a random effects panel data model (Wansbeek and Kapteyn Variance Components). Given the large number of independent variables, we dropped variables with a *t*-statistic less than 1 (this had no effect on the BP effect coefficient). The results are in Table A1.

This model indicates that oyster prices rose by $0.53 following the BP oil spill in 2010. Prices fell back to prespill 2010 levels in 2011. Evaluating each coefficient at the mean of the variable, the nonspill oyster price is $3.05 and the spill price is $3.58. We consider markup factors at the primary wholesale and processing level (82.3%), the secondary wholesale and processing level, and either retail trade from stores (33.4%) or retail trade from food service (182.4%). The total markup from harvest to consumer expenditures, ignoring value added, is 771%. Therefore, at the retail level the $0.53/lb. price difference would lead to a $4.09 price increase.

In our postspill models we examined the sensitivity of results to this additional price increase: $fp_{\text{spill}} = bp + dp_{\text{random}} + dp_{\text{BPspill}}$. Given that most oyster meals involve less than a pound of meat, we estimated the models with $1, $2, $3, and $4 values for dp_{BPspill} (rounding down from $4.09). We conducted sensitivity analysis with the price increase and found that our results are not sensitive to this difference.

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