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Stated and Revealed Preferences for Organic and Cloned Milk: Combining Choice Experiment and Scanner Data

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The U.S. Food and Drug Administration's recent announcement that milk from cloned cows is as safe to drink as that from conventionally bred cows prompted interest among farmers, food retailers, and regulators in the market impacts of the introduction of milk from clones. Because milk from cloned animals is not currently labeled in the market, we utilized a stated preference experiment to determine consumer preferences for the attribute, but also sought to determine whether the survey-based choices were consistent with people's revealed preferences given by scanner data. Our analysis indicates that a pooled model combining stated and revealed preference data exhibits overall better out-of-sample prediction performance than either data set used alone. Results from the pooled model indicate that consumers are willing to pay large premiums to avoid milk from cloned cows—an amount that is over three times that for organic or rBST-free milk. The results are used to calculate the value of a mandatory labeling program.

Key words: cloning, choice experiment, milk, organic, revealed preference, scanner data, stated preference, willingness-to-pay.

JEL codes: Q11, Q13, Q18.

Food demand analysis has traditionally utilized aggregate time-series data representing consumers' actual food purchases in the marketplace. There are at least two weaknesses of demand analyses carried out with such revealed preference (RP) data. First, the researcher has no control over the data collected. Price changes are often highly collinear, measured with error, and endogenously determined and may be confounded with changes in quality. Second, it is difficult or impossible to use RP data to infer how consumers will react to the introduction of a new good. In recent years, researchers addressed these difficulties by turning to the use of disaggregated stated preference (SP) data. SP data are useful because consumers can be asked about their willingness to purchase *any* product, including those currently unavailable in the marketplace and because the researcher controls the data collection process, ensuring that price changes are uncorrelated with other variables of interest.

That RP data lack information on consumer preferences for new varieties is particularly problematic for the question which prompted this research: how will consumers respond to the introduction of milk from cloned cows? The U.S. Food and Drug Administration (FDA 2008) concluded that "meat and milk from clones of cattle, swine, and goats, and the offspring of clones from any species traditionally consumed as food, are as safe to eat as food from conventionally bred animals." Available at http://www.fda.gov/NewsEvents/Newsroom/PressAnnouncements/2008/ucm116836.htm. With this statement, the prospect of food from cloned animals entering the marketplace became a reality. The announcement prompted some consumer groups and food retailers to implement initiatives to assuage perceived consumer concern for the technology. Several large food processors and retailers announced their intention to prohibit the sales of products from cloned animals, and in late 2007, the U.S. Senate passed legislation intended to prohibit the FDA from approving cloned products until further research was conducted (however, the final legislation that

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was signed into law only "strongly encouraged" the FDA to delay any major decision until additional studies were conducted). Understanding the economic effects of such decisions, and informing businesses and policymakers about the appropriateness of future decisions requires estimates of consumers' *willingness to pay* (WTP) for cloned products.

Previous research on animal cloning has consisted of telephone polls asking consumers questions about their knowledge and attitude toward animal cloning. For example, a study conducted for the Pew Initiative on Food and Biotechnology in 2006 found that about 65% of consumers have heard about animal cloning (Mellman Group 2006). Sosin and Richards (2005), however, reported that only about 29% of consumers believed that animal cloning was currently used by farmers and ranchers to breed animals. Storey (2006) reported that 73% of consumers had not heard about the FDA report on the use of animal cloning. The Pew study found that 29% of consumers indicated that they would be willing to purchase milk from the offspring of cloned animals, while about 33% indicated that they would never buy milk from the offspring of cloned animals. The International Food Information Council (2006, 2007) found similar results in its poll, with 41% of consumers indicating that they would be willing to purchase meat, milk, or eggs from the offspring of cloned animals in 2006; a figure which increased to 46% in 2007.

Although previous polling research has provided useful information, the results consist of purchase intentions or attitudes expressed on a five-point scale. It is difficult to use such data to determine the rate at which consumers are willing to trade concern for cloning and a desire for lower milk prices. That is, the data do not provide WTP estimates that can be used in cost benefit analysis or in making market share predictions. Moreover, a wealth of evidence indicates that such data often poorly predict actual retail behavior (Morrison 1979; Morwitz 1997).

The fact that milk from cloned cows is not currently labeled and sold in the marketplace necessarily implies that the only way to determine consumer preferences for the attribute is by using SP or experimental methods. Although SP methods permit the estimation of WTP for milk from clones, there exists ample skepticism of people's stated answers to hypothetical questions about what they *would* do when shopping. One potential way of overcoming this weakness is to combine people's SP survey answers with RP data resulting from actual market transactions in an attempt to achieve a more useful and reliable picture of consumer preferences that possess the advantages of RP data (reflecting binding choices made in real markets) and the advantages of SP data (observing choices for new products using an experimental design ensuring no confounds). Thus, although milk from cloned cattle is not currently sold in the marketplace, if the preferences expressed in an SP survey (including the attribute of cloning) are systematically related to the preferences governing choices in RP data, we might be more confident in the reliability of the estimate on consumers' preferences for cloning. Moreover, as von Haefen and Phaneuf (2008) have argued, SP data provide a means of econometrically identifying parameters that would be confounded using RP data alone.

Such logic has led researchers in recent years to combine sources of RP and SP data primarily as they relate to the valuation of environmental amenities (e.g., Adamowicz, Louviere, and Williams 1994; Adamowicz et al. 1997; Azevedo, Herriges, and Kling 2003; Huang, Haab, and Whitehead 1997) or transportation (e.g., Swait, Louviere, and Williams 1994). Louviere, Hensher, and Swait (2000) and Hensher, Louviere, and Swait (1998) provide general discussions and overviews on combining SP and RP data. A common feature among many of these studies, however, is that the RP data come from survey-based questions where people are asked to *recall* choices they previously made. Unfortunately, recall of past choices and behaviors is often inaccurate (Vazire and Mehl 2008). For example, Dickson and Sawyer (1990) showed that most grocery shoppers cannot remember the price of the item just placed in their basket. Ideally, *objective* measures of past RP choices would be used, and it is here that household scanner data are quite useful. To our knowledge, Swait and Andrews' (2003) study represents the only previous attempt to investigate whether SP data could be combined with scanner data. In an application related to laundry detergent, they found that a combined RP/SP model exhibited superior out-of-sample prediction performance relative to models fit to the SP or RP data alone.

In this paper, we seek to determine whether SP choices between milk options can be fruitfully combined with *the same household's* RP choices reflected in scanner data. The current research is similar in spirit to the Swait and Andrews (2003) study but seeks to validate their findings in a different context of current policy relevance. Whereas Swait and Andrews sought to combine SP and RP data from two different samples of individuals, we have SP and RP data from the same households, making for a "cleaner" comparison. In addition to seeking an answer to the methodological question of whether a model can be developed that predicts people's actual milk choices but that includes information on preferences for the new attribute of cloning, this work adds to the growing applied literature on people's demand for milk attributes. For example, Dhar and Foltz (2005) used store-level scanner data to estimate the consumer welfare effects of the introduction of milk free of recombinant bovine somatotropin (rBST) and labeled as organic; Kiesel and Villas-Boas (2007) used household scanner data to estimate the value of the USDA organic seal on milk; and Bernard and Bernard (2009) used experimental auctions to estimate consumer WTP for organic, rBST-free, antibiotic-free, and conventional milk. To our knowledge, no previous study has estimated consumer demand for milk from cloned versus noncloned cows; however, it is exactly this information that is currently needed by policymakers and food retailers.

Data and Methods

Our data come from 1,552 households in the Information Resources Inc (IRI) AttitudeLink™ panel. Panelists use handheld scanners to record their bar-coded purchases, which are then transmitted to IRI. In the summer of 2008, we sent an online SP survey to 4,000 households in the IRI panel: 1,691 people completed the survey, implying a response rate of 42.3%. For each of the 1,691 households, IRI provided RP home scan data on milk purchases (organic and nonorganic by fat content) aggregated over the 52-week period prior to the survey. Importantly, the RP home scan data are not based on consumers' potentially unreliable memories of past behavior but instead represent actual purchase histories.

The characteristics of the sample of respondents used in this study match up well with that of the United States as a whole, except that the sample consists of a larger share of females than is present in the U.S. population and of only primary grocery shoppers. These deviations are not terribly problematic given our focus on food choices of the primary shopper in a household.

Of the 1,691 households, 139 were not used due to incomplete information and missing scanner data, leaving 1,552 households available for analysis. From the available sample, we randomly drew data from 500 households for use in out-of-sample model validation, and data from the remaining 1,052 households are used for model estimation.

Stated Preference Data

In the online survey, panelists were asked to answer a series of discrete choice questions regarding which milk option (or none) they would buy when grocery shopping. The choice options were defined by four attributes: price per gallon ($2.99 or $5.99), fat content (whole, 2%, 1%, skim), use of rBST (no rBST used or rBST used), and use of cloning (milk from noncloned animal, milk from cloned animal, or milk from offspring of cloned animal).[1] Because some respondents might not have been knowledgeable of rBST or cloning, we included a very brief description of each. In regard to cloning, respondents were told the FDA definition: "Cloning is a complex process that lets one exactly copy the genetic, or inherited, traits of an animal. . . . [Clones] are similar to identical twins, only born at different times" (U.S. Food and Drug Administration 2009a). With regard to rBST, respondents were informed that some of the milk products indicate that they were produced with rBST, a bovine growth hormone that increases milk production in cows (U.S. Food and Drug Administration 2009b). More could have been said about both attributes; however, we felt that these brief statements would likely coincide with the information shoppers would have in a grocery store.

In constructing the choice questions, the cloning attribute was treated as alternative specific, such that option A was always "milk from noncloned animal," option B was always "milk from cloned animal," and option C was always "milk from offspring of cloned animal." Option D was added to allow people to indicate "no purchase." More specifically, option

[1] We considered including the attribute of "organic" in the SP survey; however, the attribute was ultimately excluded because we believed that respondents would find it unbelievable to find a milk option that was both organic and from a cloned cow. In fact, the USDA's National Organic Standards Board has ruled that milk from a cloned animal or from any of its offspring (or the offspring of the offspring) cannot obtain organic certification.

D stated, "If options A, B, and C were all that were available when shopping at my local grocery store, I would not purchase milk from this store." A main effects fractional factorial design was used to determine which milk options to present to respondents. Price and rBST were varied at two levels each, and fat content was varied at four levels, so that there were $2^2 \times 4 = 16$ possible combinations of milk options that could be created for each choice option A, B, and C. Because there were three milk options in each choice set, there were $16^3 = 4,096$ possible choice sets that could be constructed. From this full factorial, sixteen choice tasks were selected such that the correlations between attributes, both within and across options, were exactly zero. Each respondent answered sixteen SP choice questions, an example of which is shown in figure 1.

Revealed Preference Data

For each household, IRI provided home scan data for white milk segregated by fat content (whole, 2%, 1%, and skim) and by organic (organic and nonorganic), which implies that the RP data consist of eight possible purchase options (4 fat levels $\times$ 2 levels of organic). The RP data included total volume (gallons) purchased in the 52 weeks preceding the survey, total expenditures spent on white milk in the 52 weeks preceding the survey, and total number of units purchased in the 52 weeks preceding the survey. Purchase shares for each household were computed for each of the eight options by dividing the volume purchased of each type by the total volume of all milk purchased. Average prices ($/gallon) paid were constructed by dividing total expenditures on each milk type by volume purchased of each type. The raw means for the prices and purchase shares are shown in table 1.

Because milk prices might be correlated with unobserved quality differences, we followed the approaches outlined by Cox and Wohlgenant (1986) and Park and Capps (1997), which are predicated on the idea that price variation across households reflects differences in quality. Prices for each of the eight types of milk were regressed on region, race, income, gender, age, and average unit size purchased (total volume divided by total number of units). The estimated equation was:

$$(1) \qquad Price_{ij} = \boldsymbol{X}_i \boldsymbol{\delta}_{ij} + e_{ij}$$

where $Price_{ij}$ is the price per gallon of milk type j purchased by individual i; $\boldsymbol{X}_i$ is a vector of demographic variables described above; $\boldsymbol{\delta}_{ij}$ is a conformable vector of parameters; and e_{ij} is the residual. Quality-adjusted prices were calculated for each individual by adding the estimated intercept of equation (1) to the residuals of equation (1) (see Cox and Wohlgenant 1986; Park and Capps 1997). Households that did not purchase a particular type of milk in the preceding year were assigned a price equal to the intercept from equation (1).

Econometric Models

Based on the random utility framework, individual i's utility from choice option j is specified as a function of a systematic component assumed to depend on the attributes of the choice option (e.g., price, fat content) and a stochastic error term representing individual

Of the fresh milk options shown below, which option would you choose to purchase?

Characteristic	Option A: Milk from Noncloned Animal	Option B: Milk from Cloned Animal	Option C: Milk from Offspring of Cloned Animal	Option D
Fat content	Whole	Whole	Skim	If options A, B, and C were all that were available when shopping at my local grocery store, I would not purchase milk from this store.
Price per gallon	$5.99	$2.99	$2.99	
rBST use	No rBST used	No rBST used	No rBST used	
I would choose . . .	○	○	○	○

Figure 1. Example choice question presented to survey respondents

Table 1. Descriptive Statistics from Revealed Preference, Home Scan Data ($N = 1,552$)

Milk Type	Mean Price ($/gallon)	Mean Purchase Share
Nonorganic		
Fat free	$4.52	0.218
Low fat (1%)	$4.42	0.153
Reduced fat (2%)	$3.98	0.377
Whole	$4.63	0.214
Organic		
Fat free	$8.63	0.011
Low fat (1%)	$7.61	0.007
Reduced fat (2%)	$8.75	0.012
Whole	$8.50	0.008

idiosyncrasies unobservable to the analyst:

$$(2) \qquad U_{ij} = V_{ij} + \varepsilon_{ij}.$$

For the SP data, the systematic portion of the utility function for milk option j is:

$$\begin{aligned}(3) \qquad V_{ij} = {} & \beta_1^{sp}(Price)_{ij} + \beta_2^{sp}(whole)_{ij} \\ & + \beta_3^{sp}(1\%)_{ij} + \beta_4^{sp}(2\%)_{ij} \\ & + \beta_5^{sp}(rBSTfree)_{ij} \\ & + \beta_6^{sp}(nonclone)_{ij} + \beta_7^{sp}(clone)_{ij} \\ & + \beta_8^{sp}(clone(offspring))_{ij}\end{aligned}$$

where $(Price)_{ij}$ is the price faced by individual i for alterative j; β's are the marginal utility for the attributes; and the remaining variables are dummies indicating the presence/absence of the characteristic in question in alternative j. For identification purposes, the utility of the "none" option is normalized to zero. Given this normalization, β_6, β_7, and β_8 represent the utility of having a gallon of milk from a noncloned, cloned, and offspring-of-cloned animal, respectively, relative to not purchasing milk at all on the particular shopping occasion. Thus, the relative utility of noncloned versus cloned is $\beta 6$–$\beta 7$. For the RP data, the systematic portion of the utility function can be similarly written:

$$\begin{aligned}(4) \qquad V_{ij} = {} & \beta_1^{RP}(Price)_{ij} + \beta_2^{RP}(whole)_{ij} \\ & + \beta_3^{RP}(1\%)_{ij} + \beta_4^{RP}(2\%)_{ij} \\ & + \beta_9^{RP}(organic)_{ij}.\end{aligned}$$

McFadden (1974) shows that if the error terms in equation (2) are independent and identically distributed with type I extreme value, out of a set of J alternatives, the probability of alternative j being chosen is the familiar multinomial logit (MNL) model:

$$\begin{aligned}(5) \qquad P_{ij} & = \text{Prob(option } j \text{ is chosen)} \\ & = \frac{e^{\lambda V_{ij}}}{\sum_{k=1}^{J} e^{\lambda V_{ik}}}\end{aligned}$$

where λ is a parameter inversely related to the variance of the error term. Within a data set, λ is not separately identified from the preference parameters in equation (3) or (4) and is thus normalized to one. However, when SP and RP data are pooled, the relative magnitude of λ across data sets can be identified by setting the parameter equal to 1 in one data set and estimating the relative size of the parameter for the other data set (see Swait and Louviere 1993).

The parameters of the unrestricted (SP only and RP only) models given in equations (3) and (4) can be estimated by maximizing the respective log-likelihood functions:

$$(6) \qquad LLF^{SP} = \sum_{i=1}^{N*16}\left(y_{ij} * \ln\left(\sum_{j=1}^{4} P_{ij}\right)\right)$$

$$(7) \qquad LLF^{RP} = \sum_{i=1}^{N}\left(s_{ij} * \ln\left(\sum_{j=1}^{8} P_{ij}\right)\right)$$

where $y_{ij} = 1$ if option j is chosen by person i in the SP data set and 0 otherwise; s_{ij} is the purchase share for alternative j and household i in the RP data set; and P_{ij} is defined in equation (5).

As can be seen by comparing equations (3) and (4), the SP and RP preference functions have four common parameters related to price and milk fat content. These common parameters can be combined in a restricted (pooled) RP-SP model:

$$\begin{aligned}(8) \qquad V_{ij} = {} & \beta_1^{pooled}(Price)_{ij} + \beta_2^{pooled}(whole)_{ij} \\ & + \beta_2^{pooled}(1\%)_{ij} + \beta_4^{pooled}(2\%)_{ij} \\ & + \beta_5^{pooled}(rBSTfree)_{ij} \\ & + \beta_6^{pooled}(nonclone)_{ij} \\ & + \beta_7^{pooled}(clone)_{ij} \\ & + \beta_8^{pooled}(cloned\ offspring)_{ij} \\ & + \beta_9^{pooled}(organic)_{ij}.\end{aligned}$$

The pooled log-likelihood function is estimated by maximizing the function $LLF^{pooled} = LLF^{SP} + LLF^{RP}$, in which equation (8) acts as the underlying utility function for both SP and RP data.[2]

To determine whether the same preference structure underlies the RP and SP data, we first used an in-sample likelihood ratio test. In particular, two times the sum of the likelihood function values from the two unrestricted models subtracted from the likelihood function of the restricted (pooled) model is compared against the critical chi-square value with four degrees of freedom. The null hypothesis is that the common price and fat content parameters are equivalent across the two data sources: $\beta_1^{SP} = \beta_1^{RP}, \beta_2^{SP} = \beta_2^{RP}, \beta_3^{SP} = \beta_3^{RP}, \beta_4^{SP} = \beta_4^{RP}$.

Swait and Andrews (2003) have shown that even when the hypothesis of common preference parameters is rejected, a combined RP-SP model can exhibit superior out-of-sample prediction performance. To investigate this issue, we use the results from our estimation data set to predict the outcomes of our hold-out data set of 500 households' RP and SP choices. We consider three metrics of out-of-sample prediction performance: mean squared error (MSE), the value of the log-likelihood function evaluated at out-of-sample observations (see Norwood, Lusk, and Brorsen 2004), and the percent of out-of-sample choices correctly predicted. MSE is calculated simply as the average of the squared difference between the predicted and actual shares for each choice option. For the SP data, we do not have actual shares but rather dummy variables taking the value of 1 for options that were chosen and 0 for those options that were not chosen. A model with a smaller MSE is more preferred. The out-of-sample log likelihood function (OSLLF) is calculated by multiplying the actual share (or actual choice dummy variable) by the natural log of the predicted share for each choice option and summing these values across all choices in the hold-out data set. Models with higher OSLLF values are preferred. Finally, we say that an out-of-sample choice has been correctly predicted if the choice option that has the highest predicted share also has the highest actual share in the RP data set or was actually chosen in the SP data set.[3]

Table 2. Multinomial Logit Estimates for Stated Preference (SP) and Revealed Preference (RP) Data

Milk Attribute	Model 1, SP	Model 2, RP	Model 3, Pooled
Price	−0.424*	−1.423*	−0.437*
	(0.009)[a]	(0.053)	(0.008)
Whole vs. skim	−0.342*	−0.374*	−0.262*
	(0.037)	(0.147)	(0.029)
2% vs. skim	0.293*	0.218	0.174*
	(0.036)	(0.123)	(0.026)
1% vs. skim	0.064	−0.583*	−0.052
	(0.370)	(0.135)	(0.027)
rBST free	0.629*	–	0.638*
	(0.026)		(0.028)
Nonclone vs. none	2.385*	–	2.481*
	(0.053)		(0.046)
Clone vs. none	0.322*	–	0.422*
	(0.054)		(0.049)
Offspring of clone vs. none	0.212*	–	0.321*
	(0.053)		(0.048)
Organic	–	2.338*	0.658*
		(0.268)	(0.069)
Scale[b]			3.139
Log-likelihood	−16879.7	−712.41	−17636.54
# Parameters	8	5	10
# Obs.	16832	1052	17884

Note: Asterisk (*) represents statistical significance at the 5% level or lower.
[a]Numbers in parentheses are standard errors.
[b]The scale of the SP data set is equal to 1; the estimated value refers to the scale of the RP data set.

Results

Estimation results are shown in table 2. Models 1 and 2 are the SP-only and RP-only models. The results are consistent with expectations: people dislike price increases, prefer rBST-free

[2] Because we effectively have sixteen times more SP data than RP data, it is possible for the SP data to "dominate" the common parameters in pooled model. To account for this fact, we have also estimated pooled models where each SP choice observation is given a weight equal to 1/16. None of our primary conclusions regarding whether the data can be pooled according to in-sample tests or which model performs best in out-of-sample forecasting tests is affected by whether such weights are used. Thus, all the pooled model results presented in the paper are for the unweighted joint likelihood function.

[3] In addition to the MNL models outlined above, we estimated a more general random parameter logit (RPL) model which accounts for the repeated nature of the choice data (i.e., each household has sixteen SP choices and one RP choice) and allows for preference heterogeneity. The RPL model fits the data better in sample for the SP data but not for the RP data. Despite the good in-sample fit, the RPL models never outperform the MNL models in predicting out-of-sample choices. Because the MNL dominated the RPL in terms of out-of-sample prediction performance, we report the results of only the MNL here. Moreover, we had difficulty getting the RPL to converge with the RP data, a fact which we attribute to high correlation between prices and product characteristics in the RP data. Several authors have noted problems with empirical identifiability with the RPL in such data sets (see Cherci and Ortuzar 2008; Chiou and Walker 2007; and Walker 2002).

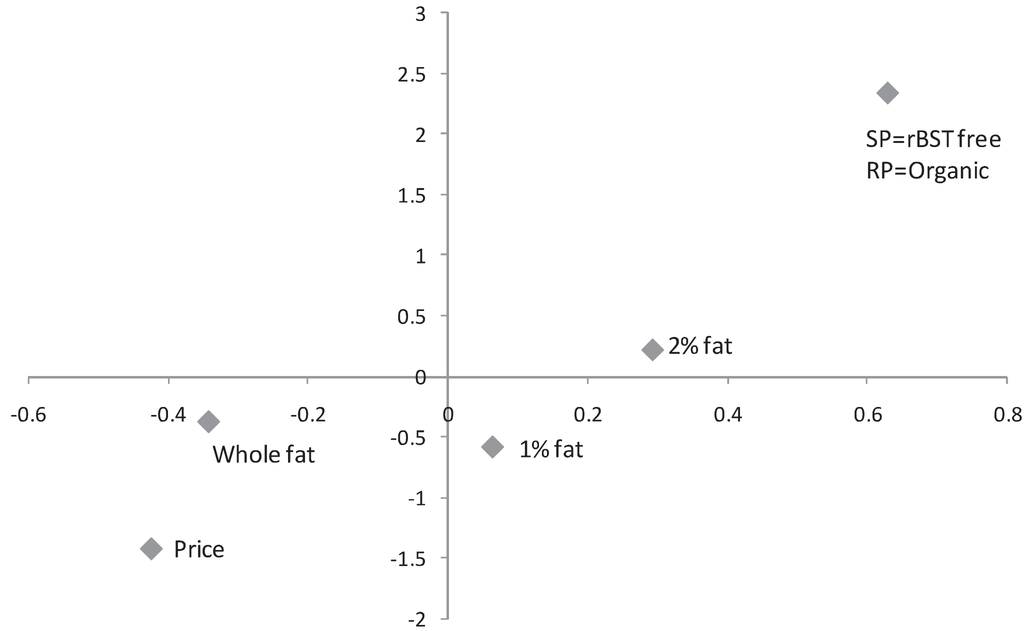

Figure 2. Relationship between parameters from revealed and stated preference multinomial logit models

to rBST products, prefer noncloned to cloned products, and prefer organic to nonorganic milk. In both data sets, whole milk is less preferred to skim and 2% is preferred to skim. However, the two data sets differ in terms of the estimated preference for 1% milk. In the RP data set (model 2), skim is preferred to 1%, but in the SP data set (model 1), people on average are indifferent between skim and 1% milk.

The third model combines the SP and RP data and estimates a pooled model where the price and fat coefficients are constrained to be equal across the two data sets while allowing for differences in error variance across the two data sets via the relative scale parameter. The log-likelihood function for model 3 (the pooled model), −17,636.54, and the sum of the log-likelihood function values for models 1 and 2, −17,592.11, are similar; however, results of a likelihood ratio test indicate that the hypothesis of equal SP and RP parameters can be rejected at the 1% significance level (i.e., the chi-square value is $2^{*}(17,636.54-17,592.11)=88.86$, which can be compared against the critical chi-square value with four degrees of freedom at the 99% confidence level, which is 13.3).

The results discussed thus far would seem to suggest little support for combining SP and RP data and might lead one to conclude that people apparently exhibit differing preferences when answering survey questions compared with shopping in grocery stores. Such a conclusion, however, might be premature. First, we ask, are the preferences displayed in the SP and RP data sets even related to one another? Figure 2 utilizes the estimates in models 1 and 2 in table 2 and plots the relationship between the common SP and RP parameters. For illustrative purposes figure 2 also plots the value of the organic parameter (in the RP data set only) against the rBST-free parameter. As can be seen in figure 2, there is clearly a positive relationship between the SP and RP preferences. In fact, the correlation coefficient between the SP and RP coefficients for the four common parameters (price and three fat content parameters) is 0.78. If we add in the rBST free and organic parameters, the correlation coefficient between the SP and RP parameters increases to 0.89. Thus, even though the in-sample likelihood ratio tests indicate that strict equality of parameters is rejected, figure 2 illustrates that the SP and RP choices are clearly related.[4]

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[4] Another way to address this question is to investigate the covariance relationship between SP and RP parameters in an RPL model. We estimated an RPL model fit to the combined SP-RP data set where none of the parameters were restricted to be equal. Of interest are the correlations between parameters that are common across the two data sets (i.e., are the people who preferred 1% milk in the SP data set the same people who preferred 1% milk in the RP data set?) and the correlations between parameters that differ across the two data sets (i.e., are the people who preferred rBST-free milk in the SP data set the same people who preferred organic milk in the RP data set?). The RPL results suggest that the SP and RP parameters are highly related. For example, the correlation between the RP price coefficient and the SP price coefficient is 0.99. The results also indicate that the same people who exhibit stronger preferences for organic milk when grocery shopping tend to be the same people who preferred rBST-free milk and were averse to

Table 3. Out-of-Sample Prediction Performance of Competing Models

Data Set Predicted	Model 1, SP	Model 2, RP	Model 3, Pooled
	Out-of-Sample Log-Likelihood		
SP	−8307.55[a]	−28710.09	−8310.03[a]
RP	−530.38	−302.74	−326.85
Pooled	−8837.93	−29012.83	−8636.88
	Mean Squared Error		
SP	0.147[a]	0.302	0.147[a]
RP	0.044	0.022	0.024
Pooled	0.136[a]	0.271	0.134[a]
	% Correctly Predicted		
SP	52.4	37.9	52.4
RP	70.8	71.2	71.9
Pooled	53.5	39.9	53.6

[a]Indicates that means in the same row with the same superscript are not significantly different at $p < 0.05$.

Figure 2 suggests the presence of some common underlying choice patterns in the SP and RP data and gives some credibility to the idea that a pooled SP-RP model might be beneficial despite the results of the in-sample likelihood ratio tests. Given that the purpose of this study is to predict what shoppers would do if and when cloned milk enters the market, it is prudent to determine the extent to which the three models reported in table 2 predict the hold-out sample of 500 households' SP and RP choices.

Table 3 reports the out-of-sample prediction performance of the three estimated models in regard to their ability to predict SP choices, RP choices, and pooled SP-RP choices in the hold-out data set (recall that out of the 1,552 individuals surveyed, data from 1,052 households were randomly selected and used for the model estimation, and the remaining 500 were used for validation). The OSLLF and MSE prediction criteria yield similar results in terms of the relative model rankings.

In terms of the OSLLF and MSE, results indicate that when predicting SP data, the SP-only model (model 1) and the pooled SP-RP model (model 3) perform equally well. The RP-only model (model 2) exhibits dismal performance in predicting hold-out SP choices. It might seem a bit strange to remark on the ability of RP data to predict SP choices, but recall that we are interested in predicting how consumers will react to the introduction of cloned milk. The RP data have nothing to say about consumer preferences for cloned versus noncloned milk, and thus it performs especially poorly in predicting SP choices. This result might be taken to imply that if cloned milk enters the marketplace, models estimated using only RP data prior to the introduction of the cloned option would yield incorrect forecasts of future market conditions.

Table 3 also shows that when predicting the RP hold-out data, the RP-only model (model 2) performs the best according to the OSLLF and MSE criteria. However, the pooled SP-RP model (model 3) fares only slightly worse than the RP-only model (model 2) in predicting RP choices. Moreover, the last three rows of table 3 indicate that the pooled SP-RP model (model 3) correctly predicts which choice was made in the SP data set equally as well as the SP-only model (model 1) and makes slightly better predictions in the RP data set than the RP-only model (model 2). The combined weight of the evidence in table 3 suggests that the pooled SP-RP model (model 3) is the preferred model. *The pooled SP-RP model predicts hold-out SP choices much better than the RP-only model and equally as well as the SP-only model, and the pooled SP-RP model predicts hold-out RP choices much better than the SP-only model and about as well or better than the RP-only model.*

What do the results from the preferred model (model 3) imply about consumer preferences for organic and rBST-free milk and for milk from cloned cattle? Table 4 reports mean WTP values for selected attributes. The reported statistics are the estimated price differences that would make a consumer indifferent between two milk options that are otherwise identical except for the attribute

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cloned milk when making stated preference choices (correlation coefficients of 0.54 and 0.05, respectively).

Table 4. Willingness to Pay for Selected Milk Attributes from Pooled SP-RP Model

Willingness to Pay ($/gallon) for . . .	
Nonclone vs. cloned	$4.71 (0.112)[a]
Noncloned vs. offspring of clone	$4.95 (0.115)
Cloned vs. offspring of clone	$0.23 (0.097)
No rBST vs. rBST	$1.46 (0.067)
Organic vs. nonorganic	$1.51 (0.161)

[a]Numbers in parentheses are standard errors estimated by parametric bootstrapping.

in question. The values are calculated by dividing the respective attribute coefficients by the negative of the price coefficient. Results reveal that consumers are willing to pay about \$1.46/gallon for rBST-free milk and about \$1.51/gallon for organic milk. These estimates are quite a bit higher than the implied premiums obtained by Bernard and Bernard (2009), who, using experimental auctions, found average WTP premiums of about \$0.15 and \$0.33 per half gallon, which are quite a bit lower than the "virtual prices" estimated for these milk types by Dhar and Foltz (2005). The results in Kiesel and Villas-Boas (2007) suggest WTP premiums for organic milk of \$1.46/gallon without the USDA seal and \$2.16/gallon with the seal.[5] Our findings are qualitatively similar to those of Bernard and Bernard (2009) in the sense that we found that people were not willing to pay much more for organic milk than for rBST-free milk despite the fact that the former implies the latter. As another point of comparison, we calculated the implied demand elasticities using the pooled model assuming a choice set consisting of four options (conventional, rBST free, organic, and "none") which in turn assume that all were noncloned and of the same fat content. Results reveal that at the prices of \$2.80, \$4.85, and \$5.91 (the average prices reported in Dhar and Foltz 2005), the own-price elasticities of demand are −0.74, −1.48, and −2.08 for conventional, rBST-free, and organic milk, respectively. These can be compared against the respective values of −1.08, −4.40, and −1.37 from Dhar and Foltz (2005) and −0.96, −4.70, and −2.34 from Bernard and Bernard (2009).

One issue addressed in this study that was not addressed in previous studies is consumer preference for cloning. As shown in table 4, people are willing to pay large premiums to avoid cloned milk: \$4.71 per gallon. This is over *three times* the amount people are willing to pay for organic or rBST-free milk. The mean WTP estimate might be interpreted with some caution given that the prices in our SP survey spanned only \$3 (from \$2.99 to \$5.99); however, we can be relatively more confident in asserting that WTP for cloned versus noncloned milk is *at least* \$3 per gallon. That said, one advantage of combining the SP and RP data is that the RP data exhibit larger price variations that more than encompass the WTP estimate (see table 1).

The results shown in table 4 also suggest that consumers do not differentiate much between milk from a clone and milk from the *offspring* of a clone. This is important because most of the cattle that are currently being cloned are for use in seed-stock and breeding, i.e., the production of *offspring* for use in commercial production. Such a high WTP value is consistent with the position of many companies that announced their intention to prohibit selling milk and meat from clones in the aftermath of the FDA announcement on the safety of food from clones.

The pooled MNL estimates can also be used to address a key policy issue: the value of a mandatory labeling system. Currently there is no way to track milk from cloned animals or their offspring, and thus most consumers are unaware whether the milk they buy is from cloned animals. In fact, in the survey, we asked respondents whether they thought products from cloned cows were already sold in grocery stores, and about 60% indicated that they did not know. Such results suggest that in the current market environment, most people are uncertain whether the milk they are buying is from cloned cows. Given this level of uncertainty, we assumed in our policy simulations that consumers currently believe they have a 50/50 chance of purchasing milk from a clone or noncloned animal when buying unlabeled milk.

To set the stage for the analysis that follows, imagine a baseline (pre-label) market environment where consumers have five choices: whole, 2%, 1%, skim (all assumed to be nonorganic, rBST free, and priced at \$4), and "none," or no purchase. We also assume that because consumers are unsure about the presence and use of cloning, their utility for each milk option is a weighted average of the cloned and noncloned utility coefficients shown in equation (8) (i.e., $0.5\beta_6^{pooled} + 0.5\beta_7^{pooled}$). In effect, we assume that when consumers go to grocery stores to buy milk, they believe that half the milk on sale is from cloned cattle and the other half is from noncloned cattle. Figure 3 shows the calculated market shares for the five choices in the assumed baseline (pre-label) condition. Results indicate that about a quarter of the shoppers chose not to purchase milk and that conditional on a purchase, 2% fat was most popular. That such a high percentage chose "none" illustrates the potential effect of uncertainty about cloning on market demand. If people are unsure whether the milk they buy is from clones, they are likely to buy less milk

[5] These results are calculated using the "after NOP" regression results reported in model 4, table 4 in Kiesel and Villas-Boas (2009).

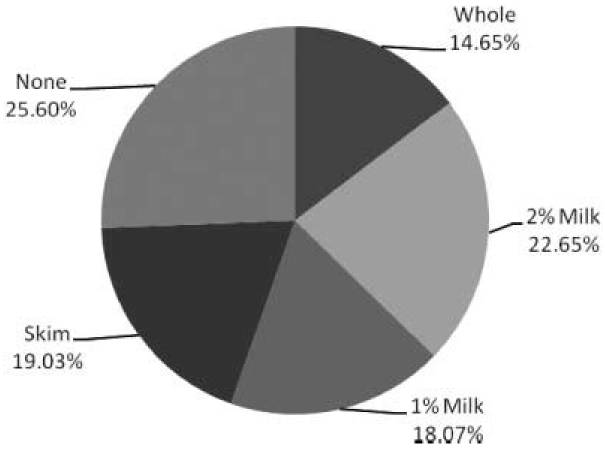

Figure 3. Market shares of milk without mandatory labeling

than they might if they knew for sure, and it is exactly this sort of reasoning that leads many to advocate mandatory labels.

The value of a mandatory labeling program depends on assumptions about how retailers will respond to the requirement and on what one assumes about current market conditions. We thus calculate the value of a mandatory labeling program under three different scenarios that make different assumptions about current and future states of nature:

- *Scenario 1:* In the pre-labeling world, it is assumed that milk from clones is actually sold in stores even though consumers believe there is a 50/50 chance (or mix) of buying cloned and noncloned milk. Retailers are assumed to respond to the mandatory labeling law by labeling all products as "may contain milk from cloned cattle."
- *Scenario 2:* In the pre-labeling world, it is assumed that milk from clones is *not* sold in stores even though consumers believe there is a 50/50 chance (or mix) of buying cloned and noncloned milk. Retailers are assumed to respond to the mandatory labeling law by labeling all products as "milk from noncloned cattle."
- *Scenario 3:* In the pre-labeling world, it is assumed that there is a 50/50 chance (or mix) of buying cloned and noncloned milk from grocery stores, and consumers' beliefs are consistent with this reality. Retailers are assumed to respond to the mandatory labeling law by creating a differentiated marketplace offering milk both from cloned and noncloned cattle.

In scenarios 1 and 2, the mandatory labeling policy does not actually change the underlying quality of the product. The labels serve simply to provide information to consumers about the choices they actually face. In these scenarios, consumers faced choices between four milk options (and none) before the policy and still face a choice between four milk options (and none) after the policy; the difference is that consumers' uncertainty about whether milk is from clones or nonclones has been resolved by the policy. However, because the actual quality of the milk has not changed, conventional welfare measures are inappropriate. Rather, the value of the mandatory labeling policy is calculated by determining the value of information, as in Hu, Veeman, and Adamowicz (2005) and Leggett (2002).

In particular, as shown by Leggett (2002), the appropriate welfare measure for scenarios 2 and 3 is:

$$(9)\quad \left[\frac{\ln\left(\sum_{k=1}^{5} e^{V_{ik}^{post-label}}\right) - \ln\left(\sum_{k=1}^{5} e^{\tilde{V}_{ik}^{pre-label}}\right)}{-\beta_1}\right] - \left[\frac{\sum_{k=1}^{5} P_k^{pre-label}\left(V_{ik}^{post-label} - V_{ik}^{pre-label}\right)}{-\beta_1}\right]$$

where β_1 is the price coefficient from the pooled model 3, P_k is the probability of choice defined in equation (5), and V_{ik} is defined in equation (8). The first term in brackets is the conventional welfare calculation except that the utility in the pre-label world, $\tilde{V}_{ik}^{pre-label}$, is based on consumers' *perceptions* of what they were buying (50/50 cloned and noncloned) rather than the actual product quality. The second term in brackets captures the value of the adjustment in choices consumers make in response to the revelation of information about milk quality. In the case of scenario 3, consumers' beliefs are assumed to be correct, $\tilde{V}_{ik}^{pre-label} = V_{ik}^{pre-label}$, and retailers are assumed to respond in such a way that consumers actually face a different set of choices. In this case, the conventional welfare measure is appropriate, and is given by:

$$(10)\quad \frac{\ln\left(\sum_{k=1}^{9} e^{V_{ik}^{post-label}}\right) - \ln\left(\sum_{k=1}^{5} e^{V_{ik}^{pre-label}}\right)}{-\beta_1}$$

where it is assumed that consumers face nine choices in the post-label world (four fat contents that are cloned and noncloned plus the none option). Whereas scenarios 1 and 2 assume constant prices pre- and post-label (because it is assumed that the actual product quality has not changed), in scenario 3 we assume that in the post-label world, milk from clones is priced at a 5% discount to noncloned milk ($3.90 vs. $4.10 per gallon) to capture the cost decreases that are likely to result from the technology.

For scenario 1, results indicate that consumers are willing to pay $0.26 per choice for a mandatory labeling system. Recall that in scenario 1, the policy serves simply to reveal to consumers that they are consuming cloned milk. Our scanner data indicate that on average, a household purchases approximately 34.93 units of milk per year (i.e., they made 34.93 choices per year). Thus, the average annual benefit per year would be approximately $9.08 per household. Given that there are 112,377,977 U.S. households (U.S. Census Bureau 2007), the total estimated annual benefit of a mandatory labeling system given the assumptions of scenario 1 would be approximately $1.021 billion.

Scenario 2 assumes that there is no cloned milk currently being sold and that the mandatory labeling policy serves simply to reveal this information to consumers. In this case, WTP for the policy is $0.19 per choice occasion, which in aggregate implies a total estimated annual benefit of approximately $746 million for scenario 2.

In scenario 3, consumers (correctly) assume that there is a mix of milk from clones and nonclones currently on the market and that retailers respond to the labeling policy by segregating the market by offering cloned and noncloned varieties for each milk fat content. Figure 4 shows the predicted market shares for the nine choices when a mandatory labeling is put into place under the assumptions outlined in scenario 3. In this case, the fraction of

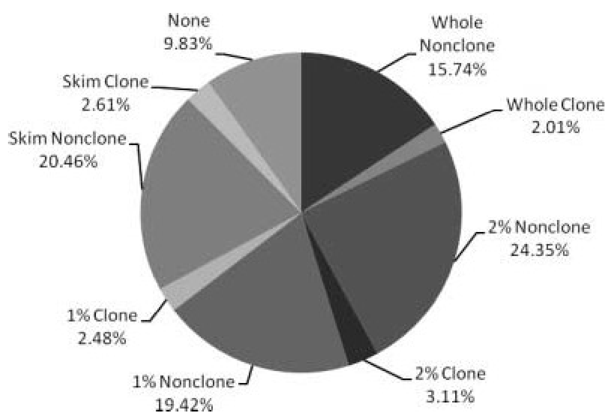

Figure 4. Market shares of milk in a segregated market with mandatory labeling

consumers predicted to refrain from purchasing milk decreases to about 10%. As compared with the prediction in figure 3, providing additional choice options to consumers is projected to increase milk consumption by approximately 16%. Using equation (10), we calculate that consumers are willing to pay $2.12 per choice occasion for a mandatory labeling system under scenario 3, which amounts to approximately $8.322 billion in aggregate.[6]

Conclusions

This study sought to determine consumer preferences for a new attribute currently unlabeled in the market (milk from cloned cows) while seeking to identify whether stated preference choices for the new attribute were congruent with people's revealed preferences given by scanner data. Although we reject the hypothesis of common preference parameters across the revealed and stated preference data sets *in sample*, our analysis suggests that a pooled model exhibits better overall out-of-sample prediction performance than either stated or revealed preference data used in isolation.

Results from the pooled RP-SP model indicate that consumers are quite averse to the use of cloning. Willingness to pay to avoid cloned milk was over three times that for organic or rBST-free milk. Additionally, we found that consumers do not differentiate between milk from a clone and milk from the offspring of a clone, a result that is important in considering the desirability of future labeling schemes. Our results also suggest that consumers would value a mandatory labeling system. We are not aware of any studies on the costs of a mandatory labeling system for cloned cattle. At the current time, a label might not be prohibitively costly, as only a few thousand clone cows are thought to be in existence; however, as technology progresses and the number of clones increases, the cost of a labeling system is likely to increase

[6] The results are based on the assumption that consumers currently assume that there is a 50/50 chance (or mix) of buying cloned and noncloned milk. If, instead, we assume that consumers currently believe there is a 40/60 chance (or mix) of buying cloned and noncloned milk, then the total estimated annual benefits are approximately $1.413 billion, $432 million, and $6.909 billion for scenarios 1, 2, and 3, respectively. If instead we assume that consumers believe there is a 60/40 chance of buying from cloned and noncloned milk, then the estimated aggregate annual benefits are $707 million, $1.178 billion, and $9.656 billion for scenarios 1, 2, and 3, respectively. The estimated benefits are not particularly sensitive to our assumptions about the prices of milk used in the policy simulations.

as well. Given these arguments, our assessment is that the labeling scenario 2 is most reflective of current realities. In this scenario, we assumed that there was no cloned milk currently being sold, although consumers were uncertain of whether this was truly the case. If retailers respond to a mandatory labeling policy by revealing to consumers that no cloned milk is in the marketplace—with labels like "milk from cows that have not been cloned"—the value of this information to consumers is $0.19 per choice occasion, or about $746 million annually in aggregate.

There are a number of interesting areas for future research. First, it would be instructive to conduct nonhypothetical experiments to determine whether WTP for cloned versus noncloned milk increases or decreases when real money and real milk is on the line. Secondly, this paper focused primarily on whether consumers' stated preferences could be combined with revealed preferences so as to obtain a more accurate estimate of the value of labeling policies related to cloning, but we did not delve into issues related to *why* consumers may be concerned about cloning technology. Finally, some of our analysis suggests a strong relationship between concern for cloning and preference for organic dairy, and future research might seek to determine whether the presence of the organic milk market is sufficient to ameliorate consumer and retailer calls for bans and labels on milk from cloned cows.

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