LINKING REVEALED AND STATED PREFERENCES TO TEST EXTERNAL VALIDITY[1]

by

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A new turn in the research agenda of environmental valuation is underway. Rather than treating stated preference (SP) and revealed preference (RP) as competing valuation techniques, analysts have begun to view them as complementary, where the strengths of each approach can be used to provide more precise and possibly more accurate benefit estimates. This turn of events began in full force with a paper by Cameron (1992a) where she combined information on the number of fishing trips in Southern Texas with responses to an SP question regarding the angler's willingness-to-pay for annual angling. She notes that the same set of preferences that generate the revealed preference data ought also to generate the stated preference data. Thus, both sources of data yield information on a common set of parameters.

There are now numerous examples of authors using both RP and SP data to jointly estimate the parameters of a preference function. A common goal of these studies has been to use the RP data to provide a benchmark against which to test the SP data for external consistency. For example, McConnell, *et al.* (1999) argue that models incorporating both revealed and stated preference data can be used to validate stated preference methods. In particular, they cite the NOAA panel report (Arrow *et al.* (1993)) in its call for using "real" behavioral willingness-to-pay data to compare with "state-of-the-art" stated preference surveys to provide external validation of the stated preference approach. Another reason for combining data sources is the increased efficiency inherent in additional information on preferences.

These applications have used a variety of modeling frameworks and forms of stated preference data. SP and RP data have been combined using both random utility models (e.g., Adamowicz, *et al.* (1994), McConnell, et al. (1999), and Hensher, Louviere, and Swait (1998)) and continuous demand functions (e.g., Dickie, *et al.* (1987), Layman, *et al.* (1996), Cameron (1992a), and Larson (1990)). In addition, two types of SP data have been used. The key difference between these types of SP data is the amount of information in the data concerning the respondents' choices. One type of SP data takes on exactly the same "look" as the RP data, and thus contains a similar amount of information (conditional on equal reliability of the two data sources). Louviere (1996) refers to models that use these two types of data as *pooling* models. Thus, standard travel cost data on prices and quantities combined with hypothetical visitation quantities at a hypothetical set of prices is a common example. Adamowicz *et al.* (1994) develop a model of this type by combining SP and RP data in a discrete choice model that uses the same explanatory variables for both the stated and revealed choice. Layman *et al.* (1996) develop a continuous model that also uses the same explanatory variables for both the stated and revealed choices. While these two papers differ in their modeling approach, they are similar in that each model is estimated using a SP and RP data set that contain the same explanatory variables. Again, it is important to emphasize that while the data sets may contain the same variables, they may not be equally reliable.

A second category of models incorporate SP data that contains different information than its associated RP data. Models that combine these types of data are referred to as *combining* models. In this case, instead of hypothetical visitation rates at proposed prices, the SP data might simply be a “yes” or “no” response to whether they would continue to visit the recreation site at the hypothetical price. This type of SP data generally contains different information than the previously described SP data, and the likelihood function used to describe it is generally of a different form than that which describes its associated RP data. Hereafter, we will refer to discrete SP data of this form as SP^D and data of the continuous type described earlier as SP^C. Examples of models where authors have combined RP and SP^D type data can be found in Cameron (1992a), Larson (1990), and Huang *et al.* (1997).

In this paper, we reexamine the models and motives for combining revealed and stated preference data. First, we note that because the different kinds of SP data contain different amounts of information, they may indicate different degrees of consistency with RP data. Specifically, stated preference questions that ask respondents whether they would continue to visit a recreation site after a price increase contains inherently less information than one that asks how many visits to the recreation site the respondent will take after a price increase. Such questions may be easier for respondents to answer, and thus yield higher response rates and possibly more accurate answers, but they contain less information. We investigate how well these two types of SP data combine with a single RP data set.

We also reconsider the interpretation of "consistent" or "inconsistent" findings of RP and SP data. We argue that while the conventional approach of treating the RP data as true and testing whether the SP data is consistent with it is intuitively appealing, it is based on the tenuous premise, that the RP data generates unbiased welfare estimates. Unfortunately, there is a compelling literature on various sources of error and bias in the RP approaches (see, e.g, Freeman (1993), Bockstael, *et al.* (1991), Smith (1993) and Randall (1994)). Thus, both sources of data are suspect and would benefit from external validation. In this context, we offer an alternative interpretation of consistency tests performed on RP and SP data. In particular, we propose three hypotheses for why the two data sources might be exhibit inconsistency: (1) SP respondents ignore their budget constraint, (2) analysts inaccurately measure the price of recreation in RP data, and (3) SP respondents do not accurately understand the contingent market proposed by the analyst. Using these hypotheses in conjunction with the jointly estimated models, we test for the presence of these effects (using the alternative model as the basis of comparison).

1. THE BEHAVIORAL AND ECONOMETRIC MODELS OF PREFERENCES

The demand model describing the RP data assumes an individual allocates income between a composite commodity (*z*) and a recreation good (*q*). The ordinary demand (Marshallian) associated with the recreation good can be written simply as

(1) $$q_i^R = f^R\left(p_i^R, y_i^R; b^R\right) + e_i^R,$$

where q_i^R is the quantity consumed by individual i, p_i^R denotes the associated price, y_i^R is the individual's income and b^R is a vector of unknown parameters. The additive stochastic term is assumed to follow a normal distribution, with $e_i^R \sim N\left(0, s_R^2\right)$. Standard econometric estimators can then be used to obtain consistent estimates of the parameters of this function accounting for censoring. Specifically, the likelihood function can be written

$$(2)\qquad LL^R = \sum_{i=1}^{n} \left\{ D_i^R \ln\left[\sigma_R^{-1} \phi\left(\frac{q_i^R - f^R\left(p_i^R, y_i^R; \beta^R\right)}{\sigma_R} \right) \right] + \left(1 - D_i^R\right) \ln\left[\Phi\left(\frac{-f^R\left(p_i^R, y_i^R; \beta^R\right)}{\sigma_R} \right) \right] \right\}$$

where Φ and ϕ are the standard normal cdf and pdf, respectively, and $D_i^R = 1$ if $q_i^R > 0; = 0$ otherwise.

1.1. Modeling SP^C data

Now suppose that in the process of gathering RP data, the survey respondents are asked "…how many recreation trips would you have taken to this site if the cost per trip increased by \$B?" The response to this question represents a form of SP^C data described above. We will have both quantity (q_i^S) and price (p_i^S) information for each individual. If, as in the case of the RP data, we assume that the survey response are driven by an underlying set of preferences, the stated demands flow from demand equations of the form $q_i^S = f^S\left(p_i^S, y_i^S; \beta^S\right) + \varepsilon_i^S$. The SP^C data can be used singly to estimate some of the parameters of the demand function or combined with the RP data to jointly estimate demand parameters.

Having constructed the log-likelihood function for the RP data, it is quite straightforward to construct it for the SP^C data since they are of identical form. Thus, the log-likelihood function in equation (2) will also describe the SP^C data, requiring only that *R* be replaced with *S* everywhere. If the RP and SP^C data are to be combined in joint estimation of preferences, efficiency would dictate that we take into account the likely correlation between the RP and SP^C responses. The log-likelihood function is given by:[2]

$$(3)\qquad \begin{aligned} LL = \sum_{i=1}^{n} \Bigg\{ & D_i^R \left[\ln\phi\left(\frac{q_i^R - f_i^R}{\sigma_R} \right) - \ln\left(\sigma_R\right) \right] + D_i^R D_i^S \left[\ln\phi\left(\frac{\left(q_i^S - f_i^S\right) - \theta^S\left(q_i^R - f_i^R\right)}{\sigma_S\sqrt{1-\rho^2}} \right) - \ln\left(\sigma_S\sqrt{1-\rho^2}\right) \right] \\ & + D_i^R\left(1 - D_i^S\right) \left[\ln\Phi\left(\frac{-f_i^S - \theta^S\left(q_i^R - f_i^R\right)}{\sigma_S\sqrt{1-\rho^2}} \right) \right] + \left(1 - D_i^R\right)\left(1 - D_i^S\right) \ln \int_{-\infty}^{\frac{-f_i^R}{\sigma_R}} \int_{-\infty}^{\frac{-f_i^S}{\sigma_S}} \phi_2\left(\eta_1, \eta_2; \rho\right) d\eta_1 d\eta_2 \Bigg\} \end{aligned}$$

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[2] The derivation of this log-likelihood function is available from the authors upon request.

where $Corr(\varepsilon_i^R, \varepsilon_i^S) = \rho$, $\theta \equiv \rho\sigma_S/\sigma_R$, $\phi_i^k = \phi^k(p_i^k, y_i^k; \beta^k)$ ($k = R, S$), and $\phi_2(\cdot,\cdot;\rho)$ denotes the standard normal bivariate pdf. This model can be used to test a variety of hypotheses concerning the consistency of the RP and SP^C data. All of the coefficients entering the SP^C portion of the likelihood can be constrained to be the same as those in the RP portion, they can all be allowed to differ, or some subset can be constrained to be equal across the data sources.

1.2. Modeling SP^D data

Suppose now that instead of providing continuous SP data, survey respondents are asked only to indicate whether or not they would take any trips to the site at issue, given a price increase of \$B. Now, instead of observing q_i^S , we observe only the discrete variable D_i^S . The underlying preferences are the same, the analyst is simply provided with less information about the consumer's underlying stated preferences. Using only the SP^D, standard probit procedures can be applied to estimate the preference parameters β^S .[3]

Combining the RP and SP^D data requires the log-likelihood function:

$$
\begin{aligned}
LL = \sum_{i=1}^{n} \Bigg\{ & D_i^R \left[\ln \phi\left(\frac{q_i^R - \phi_i^R}{\sigma_R} \right) - \ln(\sigma_R) \right] + D_i^R D_i^S \left[\ln \Phi\left(\frac{\phi_i^S + \theta(q_i^R - \phi_i^R)}{\sigma_S\sqrt{1-\rho^2}} \right) \right] \\
& + D_i^R(1 - D_i^S) \left[\ln \Phi\left(\frac{-\phi_i^S - \theta(q_i^R - \phi_i^R)}{\sigma_S\sqrt{1-\rho^2}} \right) \right] + (1 - D_i^R)(1 - D_i^S) \ln \int_{-\infty}^{\frac{-\phi_i^R}{\sigma_R}} \int_{-\infty}^{\frac{-\phi_i^S}{\sigma_S}} \phi_2(\eta_1, \eta_2; \rho)\, d\eta_1 d\eta_2 \Bigg\}.
\end{aligned}
\tag{4}
$$

2. TESTING FOR CONSISTENCY BETWEEN THE RP AND SP DATA

A primary purpose of the joint estimation of RP/SP^D and RP/SP^C models is to test whether these data sources yield consistent information on the underlying preferences of consumers. A natural approach to investigating the consistency question is to test whether the set of parameters estimated from the RP model differ in a statistical sense from the parameters estimated from each of the SP models.

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[3] Of course, if ϕ^S is linear in its parameters, only the normalized parameters β^S/σ_S will be identified.

In addition to considering this overall test of consistency, we also test whether the two sets of parameters are consistent if we allow the underlying error distributions to differ. The decision to visit a recreation site (or to take several visits in a year) is made prior to the decision to respond to the stated preference survey. Thus, the errors embedded in the data will be formed at different times and this time difference may result in a wider variance on the error from SP data relative to RP data (or vice versa). Further, the errors from the revealed portion of the data could reasonably be ascribed to errors in trip recall, random preferences, errors in the consumer's optimization strategy, or a host of possible omitted variables. In contrast, the errors in stated preference surveys are less likely to be due to recall lapse, but may have to do with the details of the survey (e.g., how the willingness-to-pay question was worded or the accuracy with which the respondent comprehended the various details of the contingent market).

Even after allowing for the possibility that RP and SP data have different error variances, there may still be differences in the parameters due to a specific bias in one of the models. For example, Cameron (1992b) proposes the combining of revealed and stated preference data to impose the "discipline of market behavior" on stated preference data. She notes that some have argued that SP respondents may ignore their budget constraint when answering willingness-to-pay questions and thus likely overstate their true values. This statement implies that the RP data could be used as a basis from which to test the validity (or bias) in the SP data. The stated preference responses can then be modeled as if the respondents viewed their income to be $y_i^S = k_y y_i^R$, $k_y > 0$, rather than their true income. The factor by which income is overstated is estimated in the joint model and, if k_y is estimated not to differ significantly from one, external validity cannot be rejected.

An alternative approach to external validity reverses the roles of the revealed and stated preference data. If the analyst believes the stated preference data are correct, but the revealed preference data are subject to error, then the stated preference data can be used as the basis for a validity test of the RP data. In particular, Randall (1994) has argued forcibly that the price term in revealed preference data is poorly measured and is likely the cause of significant bias. An external validity test of the revealed preference data can then be performed by replacing p_i^R in the linked models with $k_p p_i^R$, where $k_p > 0$. Again, if *k* is not estimated to be significantly different from one, external validity for the revealed preference data could not be rejected.

We test four different hypotheses concerning consistency:

- $H_0^1 : b^R = b^S,\ k_y = 1,\ k_p = 1,$ and $s_R = s_S$; i.e., complete consistency.
- $H_0^2 : b^R = b^S,\ k_y = 1,$ and $k_p = 1$; i.e., consistency in demand parameters but not in terms of error variances.
- $H_0^3 : b^R = b^S$ and $k_p = 1$; i.e., when respondents answer the stated preference questions, in addition to having a different error variance, they also ignore their budget constraint. Consistency holds in all other respects.
- $H_0^4 : b^R = b^S$ and $k_y = 1$; i.e., when respondents answer the revealed preference question, in addition to having a different error variance, they also do not treat the computed travel cost term (p) as the cost of accessing the recreation site (analysts have calculated the incorrect price). Consistency holds in all other respects.

In the first two cases, consistency across the two sources of data is tested, without necessarily attributing any lack of consistency to either source of data. In the latter two, one of the sources of data is taken as accurate and the second is tested against it for an indication of bias. Each of these hypotheses is tested on both the jointly estimated RP/SP^C model and the jointly estimated RP/SP^D model to determine whether the different types of SP data exhibit different characteristics concerning consistency with RP. In this regard, we note simply that the SP^D data contains less information and so we would expect it to be estimated with less precision than the SP^C data. On the other hand, because it may be easier for respondents to answer, and may therefore perform better in tests of consistency between SP and RP data.

3. AN APPLICATION TO WETLANDS IN IOWA

The model will be applied using data from a 1997 survey of Iowa residents concerning their use of Iowa wetlands. Of the 6000 surveys sent, 594 were returned by the post office as undeliverable. 3143 surveys were returned for a 59% response rate. The survey instrument elicited travel cost information, contingent behavior information in both continuous and discrete form, as well as socioeconomic information (e.g., gender, age, and income).

One section of the survey asked respondents to indicate the number of trips they had taken to each of fifteen zones over the past year, as well as the activities they engaged in during these trips.[4] This provided the RP data for our analysis. The respondents were then asked the following SP question concerning the trips they made to zones near their residence (X, Y, and Z): "Consider all of the recreation trips you made to wetlands in zones X, Y, and Z in 1997. Suppose that the **total cost per trip of each of your trips** to these areas had been $B more (for example, suppose that landowners charged a fee of this amount to use their land or that public areas charged this amount as an access fee). Would you have taken **any** recreation trips to wetlands in your zone of residence in 1997?" This question provides the discrete stated information, SP^D. They were then asked to elaborate on how many fewer trips they would have taken to each of zones X, Y, and Z. This provides the continuous stated information, SP^C. The bid values ($B) were varied randomly across the sample, ranging from $5 to $50.

The surveys provided direct information on the trip quantities. The next step was to calculate the price associated with visiting each zone as a combination of travel cost and time. We used the software package PC Miler, designed for use in the transportation and logistics industry, to establish both travel distance (d_i^z) and time (t_i^z) for each household from their residence to the center of each wetland zone. The price of visiting a given wetland zone *z* was then constructed as $p_i^z = 0.22 d_i^z + w_i t_i^z$, where w_i denotes the value of time for individual *i*. We used 25% of the individual's marginal wage rate for those employed and 10% of the marginal wage rate for those unemployed.

For the purposes of this paper, we have focused our attention on a subset of the survey sample;

i.e., those households in the Prairie Pothole region of north central Iowa (zones 4, 5, and 8). Furthermore, we consider only the aggregate number of trips to this region, with $q_i^k = q_i^4 + q_i^5 + q_i^8$ (k = R, S). The prices were formed as weighted averages of the zone specific prices, where the weights used for individual *i* were the average percentage of trips to each zone among individuals in *i*'s zone of residence. On average, for the 278 households with completed surveys in the Prairie Pothole region, 8.2 trips were actually taken, with an average price of just over $30. Respondents indicated that they would only average 2.7 trips with the hypothetical price increase to an average overall price of $57 per trip.

4. MODEL ESTIMATES AND CONSISTENCY TESTS

The parametric specification used for the demand function (1) is a simple linear representation, with $q_i^R = a^R + b_p^R p_i^R + b_y^R y_i + e_i^R$, where $e_i^R \sim N(0, s_R^2)$ and y_i denotes the household's weekly income in thousands of dollars. Similarly, for the SP data, we have $q_i^S = a^S + b_p^S p_i^S + b_y^S y_i + e_i^S$, where $e_i^S \sim N(0, s_S^2)$. Reparameterizing the model by setting $k_a^S \equiv a^S / a^R, k_p^S \equiv b_p^S / b_p^R$, etc., we obtain $q_i^S = a^R k_a^S + b_p^R k_p^S p_i^S + b_y^R k_y^S y_i + e_i^S$, $e_i^S \sim N(0, (k_s^S s_R)^2)$.

Table 1 provides parameter estimates based upon the RP and SP^C data and the log-likelihood function in equation (3). The first column corresponds to assuming that e_i^R and e_i^S are independent and the underlying preference parameters are different for the RP and SP^C responses. This would be equiva-lent to running separate models for the two data sources. For both RP and SP^C, the price and income coefficients have the expected signs and are statistically significant at any reasonable level. The intercept, price, and income coefficients are smaller for the SP^C data, with k_a^S and k_p^S individually significantly different from 1 using a 5% critical level. In contrast, the variability is estimated to be higher for the SP^C model, with

[4] The fifteen wetland zones divide the state of Iowa in areas encompassing between 3 and 12 counties and designed to encompass similar types of wetlands.

$k_s^S > 1$, but not significantly so. However, a joint test that the RP and SP^C models are in fact the same cannot be rejected at even a 20% critical level. The overall consumer surplus associated with the wetland visits is approximately $179 per trip using the fully consistent model. Similar results are obtained when we allow for correlation in the error terms between the RP and SP^C models. Column 3 provides an unconstrained model, with subsequent columns considering various hypotheses outlined in section 2. It is clear from these models that significant correlation exists between the RP and SP^C data, with r estimated to be 0.67 and significant. Yet, the fundamental is that consistency between the RP and SP^C models cannot be rejected, even at a 30% critical level.

Table 2 provides parallel results based upon the RP and SP^D data. In general, the results agree with those obtained in Table 1. Consistency between RP and SP^D models is not rejected at any reasonable critical level, in either the correlated or uncorrelated specifications.

5. FINAL COMMENTS

In this paper we have presented joint models of revealed and stated preference data that can be used to jointly estimate parameters of the underlying preference structure. The models presented are consistent with utility theory and appropriately deal with the censored sample of wetland usage in the Iowa data set and common in many other nonmarket valuation surveys. Although the various consistency tests provide just one way in which each of these hypotheses might be tested, we believe they provide some insight into the question of external validity. Still, some caveats are warranted. First, there are other specifications regarding how parameters might enter this model to reflect these hypotheses which could be proposed and tested in this framework. Further, although rejection in each of the above tests could be interpreted as rejection of the alternative hypothesis, there are likely additional explanations that are also consistent with rejection. Thus, we present the previous external validity tests not out of a belief that such tests can ever be used to validate one or the other methodologies. Rather, we believe that if enough evidence of this sort is amassed, a “preponderance of the evidence” criteria might be applied.

Table 1: RP and SP^C Models

Parameter	Uncorrelated		Correlated				
	Uncon-strained	Fully Consistent	Unconstrained	Hetero-skedasticity Hypothesis H_0^2	Price Hypothesis H_0^4	Income Hypothesis H_0^3	Fully Consistent H_0^1
a^R	17.77 (6.97)	14.95 (7.89)	17.17 (7.09)	15.62 (7.59)	15.87 (7.00)	15.20 (6.99)	15.14 (7.85)
b_p^R	-0.62 (-7.49)	-0.52 (-11.70)	-0.61 (-8.21)	-0.54 (-11.57)	-0.55 (-8.27)	-0.53 (-9.98)	-0.52 (-14.81)
b_y^R	0.12 (3.30)	0.11 (3.82)	0.12 (3.23)	0.11 (3.15)	0.11 (3.16)	0.11 (3.23)	0.11 (3.12)
s_R	13.75 (18.30)	14.21 (21.21)	14.04 (18.22)	13.91 (18.76)	13.95 (18.35)	13.85 (18.66)	14.08 (19.82)
k_a^S	0.54 (-1.97)	*1.00 (not est.)*	0.71 (-1.69)	*1.00 (not est.)*	*1.00 (not est.)*	*1.00 (not est.)*	*1.00 (not est.)*
k_p^S	0.69 (-2.00)	*1.00 (not est.)*	0.72 (-2.27)	*1.00 (not est.)*	0.98 (-0.27)	*1.00 (not est.)*	*1.00 (not est.)*
k_y^S	0.82 (-0.38)	*1.00 (not est.)*	0.72 (-0.87)	*1.00 (not est.)*	*1.00 (not est.)*	0.85 (-0.60)	*1.00 (not est.)*
k_s^S	1.10 (0.83)	*1.00 (not est.)*	0.99 (-0.15)	1.05 (0.67)	1.04 (0.49)	1.06 (0.76)	*1.00 (not est.)*
r	---	---	0.67 (15.63)	0.68 (15.79)	0.68 (15.72)	0.68 (15.69)	0.68 (15.79)
-log L	1195.78	1198.27	1145.68	1147.68	1147.64	1147.50	1147.92
CS^R	149.78	178.63	152.21	172.00	168.14	177.01	178.61
CS^S	217.64	178.63	211.43	172.00	171.42	177.01	178.61
P-values	---	0.22	---	0.26	0.14	0.16	0.35

The t-statistics are in parentheses below the coefficient estimates. T-statistics for *k* parameters are tests of departures from one.

Table 2: RP and SP^D Models

Parameter	Uncorrelated		Correlated				
	Unconstrained	Fully Consistent	Unconstrained	Heteroskedasticity Hypothesis H_0^2	Price Hypothesis H_0^4	Income Hypothesis H_0^3	Fully Consistent H_0^1
a^R	17.77 (6.97)	16.04 (8.43)	17.38 (7.36)	16.88 (7.25)	17.41 (7.13)	17.37 (7.03)	15.91 (8.07)
b_p^R	-0.62 (-7.49)	-0.54 (-12.12)	-0.62 (-8.90)	-0.59 (-8.53)	-0.62 (-7.87)	-0.61 (-7.99)	-0.55 (-14.16)
b_y^R	0.12 (3.30)	0.11 (3.88)	0.12 (3.24)	0.12 (3.28)	0.12 (3.34)	0.12 (3.20)	0.11 (3.27)
s_R	13.75 (18.30)	13.81 (18.71)	14.04 (19.06)	13.93 (19.37)	14.04 (18.91)	14.00 (19.06)	13.94 (19.48)
k_a^S	0.85 (-0.54)	*1.00 (not est.)*	0.93 (-0.32)	*1.00 (not est.)*	*1.00 (not est.)*	*1.00 (not est.)*	*1.00 (not est.)*
k_p^S	0.86 (-0.79)	*1.00 (not est.)*	0.87 (-0.94)	*1.00 (not est.)*	0.94 (-0.76)	*1.00 (not est.)*	*1.00 (not est.)*
k_y^S	0.95 (-0.09)	*1.00 (not est.)*	0.90 (-0.24)	*1.00 (not est.)*	*1.00 (not est.)*	1.18 (0.56)	*1.00 (not est.)*
k_s^S	*1.10 (not est.)*	*1.00 (not est.)*	*0.99 (not est.)*	1.16 (0.79)	1.07 (0.35)	1.15 (0.80)	*1.00 (not est.)*
r	---	---	0.61 (11.02)	0.61 (11.01)	0.61 (11.01)	0.61 (11.01)	0.61 (11.04)
-log L	940.98	941.74	910.22	910.47	910.22	910.30	910.81
CS^R	149.77	170.96	150.00	156.76	149.98	151.87	170.01
CS^S	---	170.96	165.96	156.76	159.10	151.87	170.01
P-values	---	0.68	---	0.78	0.96	0.69	0.75

The t-statistics are in parentheses below the coefficient estimates. T-statistics for *k* parameters are tests of departures from one.

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