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Research Article

Customer Satisfaction and the Consumption Function

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This paper evaluates the extent to which the American Customer Satisfaction Index (ACSI) acts as a determining variable of the US consumption function. Results show that the ACSI is a significant self-predictor of personal consumption expenditure, as well as a potent policy variable even when income and wealth are controlled for.

1. Introduction

The Consumer Confidence Index (CCI) is regularly reported in the media to show the general mood of consumers as regards the future. Intuitively, when economic prospects are uncertain, households tend to reduce their consumption and vice versa during economic booms. Carrol et al. [1] and Desroches and Gosselin [2] explain that the CCI has a direct role in consumption expenditure because of its predictive power as well as an indirect effect by influencing the future income perception of consumers. On its own, the CCI tends to explain about 14 percent of the variation in personal consumption expenditure (PCE) [1]. Bryant and Macri [3] go further to theorize that if confidence is a monotonically increasing function of future income, then future consumption is a function of current CCI, and current consumption is a function of lagged CCI. Thus, consumer confidence is well established as an important determinant of PCE. However, as a policy variable, the CCI is difficult to manipulate as consumers are inundated with various information to make their own judgment as per the future.

In this paper we propose a measure that is potent enough to become a policy variable – consumer satisfaction. Despite two decades of research in customer satisfaction and a seminal article on the American Customer Satisfaction Index (ACSI) by Fornell et al. [4], the importance of the construct remains at the firm level [5–7]. Until recently, economists have shied away from this area of research. This is despite Fornell et al.'s [4, page 15], allusion that customer satisfaction has the "potential to be a useful tool for evaluating and enhancing the health of the nation's economy, both in terms of national competitiveness and the welfare of its citizens". In a very recent paper, Fornell et al. [8] argue that lagged gross consumption utility (represented by customer satisfaction) does indeed affect consumer discretionary spending.

The theoretical justification of the link between customer satisfaction and national consumption is quite obvious. Fornell et al. [4] argue that customer satisfaction is a driver of consumption expenditure because it measures the quality of economic output. When consumers are satisfied with their previous purchases, their willingness to spend would increase and vice versa. In this regard, customers' views on satisfaction are perhaps more reliable than confidence indicators as the former is based on actual experience with the product while the latter relies on perception. Similarly, actions taken by firms to improve satisfaction and policies that ensure that firms allocate sufficient resources to this action are more easily monitored compared to efforts to raise consumer sentiments. One produces direct results while the other is still dependent on the whims and fancies of the consumer.

In this study we compare the extent to which the CSI and CCI act as determining variables in the national consumption function, given traditional factors like personal income and wealth. In addition, we consider the impact of a change in CSI on various categories of PCE including

Durables, Nondurables, and Services. We do this for the US economy simply because of the intensive data collection efforts undertaken by the University of Michigan's National Quality Research Center to produce the time series [4]. In this regard, we confirm and further extend the work of Fornell et al. [8].

2. Methodology and Data

The robustness of the CSI as a policy tool is assessed in this paper by evaluating its predictability—both its self-forecasting capacity and its incremental forecasting capacity—on PCE. We compare the predictability of CSI by controlling other variables like income and CCI. We replicate Carrol et al.'s [1] methodology which examined the predictability of the CCI for the US economy. Other economists have also mirrored their methodology and benchmarked against the results of Carroll et al. (for instance, Desroches and Gosselin [2], Bryant and Macri [3], and Fan and Wong [9]). Carrol's methodology involves two steps. The first step examines the self-forecasting capacity of an index (S) by fitting

$$\Delta \log(C_t) = \alpha_0 + \sum_{i=1}^{n} \beta_i S_{t-i} + \varepsilon_t, \tag{1}$$

where C denotes various categories of consumption (e.g., total consumption, durable, nondurable, services, etc.) and S denotes the selected index, respectively. The second step examines the incremental forecasting capacity of S by fitting

$$\Delta \log(C_t) = \alpha_0 + \sum_{i=1}^{n1} \beta_i S_{t-i} + \sum_{i=1}^{n2} \gamma Z_{t-i} + \varepsilon_t, \tag{2}$$

where Z_t are four lags of the growth of real labor income (ΔRLI). In both steps, R^2s and incremental R^2s were examined to address the predictability of the index on consumption measures. Both Carrol et al. [1] and Fan and Wong [9] suggested that the selection of other variables to be included in the equation as control variables is inherently somewhat arbitrary, although this is refuted by Bryant and Marci [3]. In this study we first follow Carrol et al. and use the growth of real labor income as Z in (2). (Indeed, apart from using ΔRLI, we attempted other income-related variables such as $\Delta \log(\text{RLI})$, $\Delta \log(\text{PDI})$, and $\Delta \log(\text{GDP})$ as the control variable in (2). All these variables have similar predictability and thus we agree with Carrol et al. and Fan and Wong that the selection of the control variable for the purpose of this study is inherently somewhat arbitrary.) Real labor income is defined as wages and salaries plus transfers minus personal contributions for social insurance. In addition, we examine the incremental forecasting capacity of CSI after controlling the effects of CCI on the various categories of PCE. This would further validate the notion that CSI provides incremental information. In another words, ΔRLI is replaced by CCI as the controlling variable in (2) so that we can examine if CSI's forecasting capacity on PCEs is competed away by other macro customer metrics.

Both Carrol et al. and Fan and Wong included four lags in their fitted equation. Our study examines if the selection of the most appropriate lags (by using AIC) would produce different results. Later, an extension of Carrol et al.'s analysis is attempted by including wealth variables.

Quarterly time series from 1994 : 3 to 2007 : 2 for the variables used in this study were collected from various sources. They are (1) personal consumption expenditure (PCE) and their respective categories, (2) real labour income (RLI), (3) personal disposable income (PDI), (4) consumer confident index (*CCI*), (5) customer satisfaction index (CSI), (6) house price index (HMW), and (7) the S&P index (SMW). Items (1)–(3) were collected from the US Bureau of Economic Analysis; items (4) and (5) were collected from Reuters/University of Michigan's Survey of Consumers (http://www.sca.isr.umich.edu/) and the American Customer Satisfaction Index (http://www.theacsi.org/), respectively. Items (6) and (7) were collected from the Standard & Poor's (http://www.standardandpoors.com/) and the Office of Federal Housing Enterprise Oversight (ofheo.gov), respectively. The descriptive statistics of the selected variables (level data) and their correlations are displayed in Table 1.

3. Results of Analysis

In terms of the self-forecasting capacity of the selected index (1), our results (Table 2) show that the CCI has some forecasting capacity on the total, nondurable and particularly services consumption, while the CSI has some forecasting capacity on all categories of consumption measures except nondurable consumption. (To an extent, this result supports Fornell et al. [8] which used discretionary consumption as the dependent variable.) There is no significant difference regardless whether four lags or the optimum lag is selected. The forecasting capacity of CSI is relatively strong on total consumption but quite moderate on other consumption categories—it explains 17.7% variations of total consumption. Thus, it appears that CSI can be used to predict a wider range of consumption categories.

Prior to estimating (2), we need to consider if Hall's random walk hypothesis in which no lagged variable should have any predictive power for consumption applies. In particular, we test if the six consumption categories can be predicted by the lagged PDI. Akaike info criterion (*AIC*) points to the first lag as the most appropriate lag length for all consumption categories. At the 10% significance level, four of the six consumption categories can be predicted by the lagged PDI. The R^2 ranged from 5% to 11%. Therefore, Hall's hypothesis is rejected, and lagged variables should have some predicting power on PCE.

We now proceed to evaluate the predictive capacity of CCI and CSI. Table 3 reports two information obtained from fitting (2): the differences in adjusted R^2s of the fitted equation (2) before and after the inclusion of $\sum_{i=1}^{n} \beta_i S_{t-i}$ and the P-values of the joint significance of $\sum_{i=1}^{n} \beta_i S_{t-i}$. As mentioned previously, (2) is used to examine the incremental information the two indices provide to predict changes in consumption. We examine the difference between the

Table 1: Descriptive statistics of data collection and their correlations.

	(1)	(1a)	(1b)	(1c)	(2)	(3)	(4)	(5)	(6)	(7)
(1) PCE	1									
(1a) PCE-Durable	0.998	1								
(1b) PCE-Nondurable	0.997	0.995	1							
(1c) PCE-Service	0.999	0.996	0.995	1						
(2) RLI	0.998	0.993	0.997	0.998	1					
(3) PDI	0.995	0.992	0.989	0.996	0.992	1				
(4) CCI	−0.393	−0.393	−0.414	−0.387	−0.382	−0.347	1			
(5) CSI	0.449	0.457	0.487	0.433	0.438	0.432	−0.529	1		
(6) HMW	0.956	0.952	0.974	0.950	0.961	0.934	−0.497	0.559	1	
(7) SMW	0.687	0.677	0.667	0.694	0.702	0.709	0.292	−0.014	0.556	1
Mean	6715.5	866.5	1958.1	3900.1	5151152.0	25190.7	95.2	73.1	264.0	1050.9
Std. Dev.	886.1	217.4	233.8	437.1	962158.3	2019.5	7.9	1.0	70.3	288.4
Min	5305.7	529.1	1610.6	3185.8	3567556.0	21870.0	80.0	70.7	183.4	459.3
Max	8215.7	1223.2	2386.6	4630.7	6981739.0	28595.0	110.1	75.2	409.1	1498.6

Table 2: Self-forecasting capacity of CCI and CSI.

	S = CCI		S = CSI	
Consumption	R^2	P-values of the joint significance of $\sum_{i=1}^{4} \beta_i S_{t-1}$	R^2	P-values of the joint significance of $\sum_{i=1}^{4} \beta_i S_{t-1}$
Total PCE	0.175	0.043**	0.177	0.005***
Durable	0.068	0.639	0.081	0.010***
Motor	0.087	0.437	0.076	0.038**
Durable without motor	0.003	0.994	0.058	0.082*
Non-durable	0.163	0.024**	0.037	0.653
Service	0.320	0.000***	0.145	0.040**

Table 3: Incremental forecasting capacity of CCI and CSI.

Panel (a) Estimations of (2), Four lags are used						
	S = CCI, Z = ΔRLI		S = CSI, Z = ΔRLI		S = CSI, Z = CCI	
Consumption	Incremental adjusted R^2	P-values of the joint significance of $\sum_{i=1}^{4} \beta_i S_{t-i}$	Incremental adjusted R^2	P-values of the joint significance of $\sum_{i=1}^{4} \beta_i S_{t-i}$	Incremental adjusted R^2	P-values of the joint significance of $\sum_{i=1}^{4} \beta_i S_{t-i}$
Total PCE	0.140	0.010**	0.100	0.098*	0.031	0.358
Durable	0.099	0.016**	−0.022	0.073*	0.015	0.545
Motor	0.110	0.012**	−0.030	0.341	0.002	0.446
Durable w/o. motor	−0.076	0.828	−0.021	0.007***	−0.025	0.905
Non-durable	0.117	0.054*	−0.059	0.628	−0.042	0.867
Service	0.102	0.000***	0.083	0.000***	0.009	0.264
Panel (b) Estimations of (2), with optimum lag						
	S = CCI, Z = ΔRLI		S = CSI, Z = ΔRLI		S = CSI, Z = CCI	
Consumption	Incremental adjusted R^2	P-values of the joint significance of $\sum_{i=1}^{4} \beta_i S_{t-i}$	Incremental adjusted R^2	P-values of the joint significance of $\sum_{i=1}^{4} \beta_i S_{t-i}$	Incremental adjusted R^2	P-values of the joint significance of $\sum_{i=1}^{4} \beta_i S_{t-i}$
Total PCE	0.149	0.001***	0.136	0.003***	0.094	0.029**
Durable	0.058	0.006***	0.053	0.007***	0.032	0.085*
Motor	0.069	0.011***	0.035	0.037**	0.037	0.080*
Durable w/o. motor	−0.015	0.678	0.012	0.061*	0.027	0.205
Non-durable	0.108	0.022**	0.010	0.161	−0.002	0.417
Service	0.156	0.000***	0.113	0.000***	0.035	0.089*

***, **, and * denote 1%, 5%, and 10% significance levels, respectively.

adjusted R^2 from the consumption function with only the control variable as the independent variable and the adjusted R^2 when both the control variable and CCI or CSI are included as independent variables. Panel A reports the results when four lags are used; panel B replicates the results when the optimum lag length is used. Adjusted R^2 is reported here to control for the exaggeration of R^2 that is caused by increasing the number of independent variables.

For most cases, the models fitted by using the optimum lag length produce relatively higher incremental adjusted R^2. Particularly for the CSI, the use of optimum lag length turns negative incremental adjusted R^2 to positive. Using the optimum lag length also increased estimation efficiency by reducing degrees of freedom. Given all these, all interpretations will be based on Panel B. For CCI, except for durable without motor, the inclusion of the index improves the predictability of the fitted equations. The effects are relatively strong on total consumption and service consumption. For CSI, the predictability remains high for a wide range of consumption categories. The result also confirms that it has no predictability on nondurable consumption as showed in Table 3. Comparing to CCI, the added contributions to the equation made by CSI appear slightly less than CCI. In general, both CCI and CSI have some incremental forecasting capacity on more than one type of consumption categories but in terms of the size of predictive power CCI is relatively stronger when compared to CSI. Given CCI's predictability on PCEs, CSI's effects on PCEs could be competed away when CCI is included as the controlling variable. In this regard, however, CSI remains significant in 4 out of 6 PCE variables (Total PCE, Durables, Durables with Motor, and Services) at the 10% significance level. However, the incremental adjusted R squares are small, ranging from 3.2 to 9.4%. Our results are markedly different from those of Fornell et al. [8] who found the consumer sentiment variable to be insignificant when both sentiment and satisfaction indices were included in the consumption function.

We take the analysis a step further by (1) including wealth variables into our consumption equation and (2) incorporating both short-term and long-term behavior of consumption into a single equation. (In this context, our study is slightly different from that of Fornell et al. [8] as they used the debt service ratio to represent income (or ability to pay). The selection of the income variable is arbitrary as previous consumption function research has used both types of variables to measure income.) The former is carried out by including financial and housing wealth while the latter is done by establishing an error correction model (ECM) as in

$$\begin{aligned}\Delta\log(\mathrm{PCE}_t) = {} & \alpha_0 + \beta_1\Delta\log(\mathrm{PCE}_{t-1}) + \beta_2\Delta\log(\mathrm{PDI}_t) \\ & + \beta_3\Delta\log(\mathrm{SMW}_t) + \beta_4\Delta\log(\mathrm{HMW}_t) \\ & + \beta_5\mathrm{ECT}_{t-1} + \varepsilon_t,\end{aligned} \tag{3}$$

where SMW and HMW represent the stock market wealth (representing financial wealth) and house market wealth, respectively. We use the S&P index and house price index to measure these wealth indicators. The error correction term is given by

$$\begin{aligned}\mathrm{ECT} = {} & \log(\mathrm{PCE}_t) - \delta_0 - \gamma_1\log(\mathrm{PCE}_{t-1}) - \gamma_2\log(\mathrm{PDI}_t) \\ & - \gamma_3\log(\mathrm{SMW}_t) - \gamma_4\log(\mathrm{HMW}_t).\end{aligned} \tag{4}$$

ECT is actually the residual series resulting from regressing $\log(\mathrm{PCE}_t)$ on $\log(\mathrm{PCE}_{t-1})$, $\log(\mathrm{PDI}_t)$, $\log(\mathrm{SMW}_t)$, and $\log(\mathrm{HMW})$; δ_0 and γs are estimated by the same equation.

The ECM has an added advantage in that it transforms all variables into stationary ones and thus avoids the unit root problem. It also serves as a means of reconciling the short-run behavior of an economic variable with its long-run behavior [10].

The estimations are given by

$$\begin{aligned}\Delta\log(\mathrm{PCE}_t) &= \underset{(0.002)}{-0.001} \; \underset{(0.220)}{+0.876\Delta\mathrm{PCE}_{t-1}} \; \underset{(0.058)}{+0.095\Delta\mathrm{PDI}_t} \; \underset{(0.006)}{+0.017\Delta\mathrm{SMW}_t} \; \underset{(0.054)}{+0.055\Delta\mathrm{HMW}_t} \; \underset{(0.271)}{-1.275\mathrm{ECT}_{t-1}} \\ \mathrm{P} &= 0.397 \quad 0.000 \quad 0.054 \quad 0.003 \quad 0.156 \quad 0.000, \\ R^2 &= 0.380;\ \mathrm{Adj}.R^2 = 0.311;\ \mathrm{DW} = 2.046; \\ \mathrm{RESET} &= 1.11\ (0.291);\ \mathrm{LM} = 2.105\ (0.147);\ \text{Jarque-Bera} = 0.716\ (0.699), \\ \mathrm{ECT} &= +0.263 - 0.883\log(\mathrm{PCE}_{t-1}) - 0.114\log(\mathrm{PDI}_t) - 0.009\log(\mathrm{SMW}_t) - 0.016\log(\mathrm{HMW}_t)\end{aligned} \tag{5}$$

All terms here are stationary and as such the model has both long-run and short-run properties built into it. The fitted model is stable, well specified as shown by the diagnostic statistics. Next, $\Delta\log(\mathrm{CCI}_t)$, $\Delta\log(\mathrm{CCI}_{t-1})$, $\Delta\log(\mathrm{CSI})$, and $\Delta\log(\mathrm{CSI}_{t-1})$ are entered into the fitted equation one at time in order to examine the significance and impact of consumer confidence and satisfaction on consumption expenditure. Our results show that the lagged variables of both indices are significant with a coefficient of 0.021 and 0.16, respectively. This suggests that a one percent increase in the growth of CCI or CSI in the last period will increase the growth of the current period PCE by 0.021 and 0.16 percent, respectively. In other words, the effects of CCI and CSI are not competed away by other stronger determinants of PCE in the fitted equation. Considering these and previous results, we conclude that the effects of the indices are quite robust and their significances have not occurred by chance.

4. Discussion and Conclusion

In this study we find CSI to be a significant predictor of PCE. However, compared to CCI, the CSI can be a more viable policy option. As the CCI is an indication of consumers' impression of future economic conditions, it involves coaxing the public into believing that the future is indeed looking bright, rightly or wrongly. This is perhaps more political, and success cannot be guaranteed. On the other hand, the CSI can be improved through systematic efforts by policy makers. Since the link between customer satisfaction and firm performance has been clearly established in previous literature, the role of the government would be to nudge firms towards improving their efforts in enhancing customer satisfaction. This could take many forms, including creating a ranking of firms according to a national CSI, incentivizing (or penalizing) firms with high (low) CSIs, empowering consumer associations to become watchdogs of company actions, and setting standards that include safety, quality, and after-sales service.

Although the results of the present study are in general in line with Fornell et al.'s [8] work, our study provides more details on the effects of CSI on PCE as our investigation included different categories of PCE variables. In this regard, the significance of the CSI as a policy variable is further enhanced because of its effect on the various categories of PCE. Our results show that the self-forecasting capacity of CSI has a significant impact on the change in durable goods and services, compared to CCI which has a significant effect on non-durables. Given that durables have a greater significance on macroeconomic performance—due to their proportion to total PCE as well as to its intertemporal volatility—efforts at improving CSI would prove to be a more significant policy tool compared to the CCI. It should be noted, however, that both the CCI and CSI have a time lag in its effect. Our results show that an increase in the CSI in the last quarter will have a significant positive effect on PCE in the current quarter. Thus, when using the CSI as a policy tool, sufficient time should be allocated for the policy to take full effect.

More robust consumption functions for the US as well as other regions need to be employed to affirm our findings. Specific efforts by policy makers to enhance CSI need to be identified. The role of CSI at the different stages of the business cycle needs to be considered. Taken together, our findings as well as that of Fornell et al. [8] provide sufficient evidence that further work in this neglected area is warranted.

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