DOCFRADIS

COLECCIÓN DE DOCUMENTOS DE TRABAJO
CATEDRA FUNDACIÓN RAMÓN ARECES
DE DISTRIBUCIÓN COMERCIAL

DOC 50

Fecha Publicación: 18/05/2017

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Does Aggregate Buyer Satisfaction affect Household Consumption Growth?

ABSTRACT

This study finds that measures of the University of Michigan's American Customer Satisfaction Index are related to Personal Consumption Growth, controlling for typical predictors that are commonly included in the Index of Leading Indicators. In assessing the relationship, this study uses a Bayesian mean-variance regression that addresses problems of small sample sizes and non-normal distributions by considering both parameter and distributional uncertainty in a semi-parametric framework. Importantly, this paper introduces a new psychometric measure to assess consumer satisfaction; variants of this measure are gaining acceptance in the private and public sectors in Scandinavia, China, Japan, Korea, the United States and in other countries

Keywords: Customer satisfaction, Personal consumption growth

JEL classification: M31, D14

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ISSN: 2253-6299
Depósito Legal: AS-04989-2011
Edita: Cátedra Fundación Ramón Areces de Distribución Comercial de la Universidad de Oviedo

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1. INTRODUCTION

Understanding consumption growth – its predictors as well as its consequences for the material well being of society – is a major challenge of considerable importance. The largest proportion of all economic transactions involves consumers and thus their spending has a large impact on the economy. In this study, we examine the effect of present aggregate consumer satisfaction on future consumer spending. By using new psychometric measures and data sources, we attempt to shed light on a long-standing question: Does gross consumer satisfaction predict consumer spending (and thus GDP growth)?

Consistent with Hall's (1978) analysis of Milton Friedman's (1957) Permanent Income Hypothesis, prediction of consumer spending has been difficult. Hall (1978) finds that the Permanent Income Hypothesis implies consumption is a random walk and that the best prediction of future consumption is present consumption; this may perhaps have discouraged further attempts to predict spending from other variables. Flavin (1981) and Campbell and Mankiw (1989) further add to this problem by indicating the "excess sensitivity" of consumption. In addition, empirically it has been difficult to predict consumer spending from such variables as income, employment, consumer debt, and tax rebates (Case et al., 2005; Murphy, 2000; Shapiro and Slemrod, 2003). Whereas these variables measure consumers' "capacity to spend," Katona (1979) asserts that this capacity to spend is a necessary but not sufficient for the prediction of actual spending. "Willingness to spend," according to Katona, is critical as a motivator of spending behavior.

Attempts to predict consumption growth from measures of consumers' willingness to spend have however been limited, which may have in part been caused by the necessity to measure it from survey data. One notable exception is the University of Michigan's Consumer Sentiment Index, which began in the 1940s and is now included in the Index of Leading Indicators, published by the Conference Board, which also produces the Consumer Confidence Index. The Consumer Sentiment Index is a monthly measure, based on telephone interviews of approximately 6,000 individuals per year. In an early study, Hymans (1970) reports, however, that the Sentiment Index is of marginal value in explaining automobile and non-durable sales. This finding has been supported in research by Burch and Gordon (1984) and Kamakara and Gessner (1986). From the relatively large number of empirical studies that have been done to date (Curtin, 2004), the emerging consensus seems that the Sentiment

Index is potentially useful in explaining consumption; however, although there is a statistically significant relationship between lagged values of the Consumer Sentiment Index and consumer spending growth its predictive ability is limited (Throop, 1992; Carroll, Fuhrer, and Wilcox, 1994; Bram and Ludvigson, 1998; Howrey and Lovell, 2001; Desroches and Gosselin, 2002; Slacalec, 2003; Ludvigson, 2004). Further, the underlying causes for the empirical relationship have not been well documented. One possible explanation is that higher levels of consumer confidence about the future should lead to less savings and lower consumption growth in the future. But, Carroll, Fuhrer, and Wilcox (1994), Bram and Ludvigson (1998), and Ludvigson (2004) argue that the Consumer Sentiment Index does not reflect precautionary savings motives, whereas Souleles (2004) reports the opposite. Ludvigson (2004) concludes that the question of why consumer sentiment may help predict future consumption growth remains unresolved.

This study looks into a new consumer survey measure – the American Customer Satisfaction Index (*ACSI*) – which appears to hold promise for the prediction problem. Not until recently has data on consumption utility or consumer satisfaction become available. Like the Consumer Sentiment Index, the *ACSI* measure comes from the University of Michigan. *ACSI* is based on surveys of customers' satisfaction in seven economic sectors. On average, the annual sample size is about 70,000 individuals. Measures of satisfaction may predict spending because consumer expenditure reflects the valuation of satisfaction from the products and services previously bought.

While it seems apparent that the satisfaction people get from shopping, buying, and consuming must have something to do with their future discretionary spending, the nature of that relationship has not been extensively investigated. Likewise, although at a macro-level higher buyer satisfaction should shift demand upwards, the question of how at a micro-level satisfaction translates into an inter-temporal macro effect of overall spending remains unknown. A tentative explanation comes from recent studies (Berns, 2005; Camerer, Loewenstein, and Prelec, 2005) that have shown that intertemporal choices are governed by the interplay between cognitive and affective systems in the human brain. Greater activity of the affective system is associated with more discounting of the future, and increased desire for instant gratification. Higher levels of satisfaction are produced by greater levels of activity of the affective system and are associated with a greater probability that the individual seeks to repeat the experience which produced such satisfaction. Accordingly, we should observe effects of increasing satisfaction within relatively short periods of time for most products. These studies suggest that consumption choice results from competition between the immediate satisfaction of acquisition and the pain of paying (Prelec and Loevenstein, 1998). It is this mechanism that gives rise to satisfaction as a prime driver of consumption (Knutson, Rick, Wimmer, Prelec, Loewenstein, 2007), but we conjecture that increased satisfaction levels may not only result in increased levels of spending, but also higher volatility of spending growth.

These theoretical predictions notwithstanding, from a methodological point of view there are several potential problems when modeling *ACSI's* effects on spending. First, its time series is relatively short with quarterly observations going back only to 1995, so that the amount of data available for estimation is limited. A second difficulty is that the population distribution of the satisfaction index is not normal. Thus, inferences using classical analyses might suffer from considerable uncertainties and biases in the estimates of the parameters due to the limited information in the data as well as the distributional properties of the errors. Third, shifts in aggregate satisfaction levels may not only cause shifts in the expenditure levels, but also in its volatility. To address these three problems we develop a semi-parametric Bayesian mean-variance regression model that considers both parameter and distributional uncertainty in a framework. We show that, with this methodology, sufficient information has accumulated to assess the relationship between spending and consumption growth empirically and we find that changes in *ACSI* are indeed related to consumption growth.

2. DATA

For personal consumption expenditure (*PCE*) growth we use quarterly series measured in chained 1996 dollars provided by the Bureau of Economic Analysis (BEA). As a control variable, we use the Index of Leading Indicators (*ILI*) from the Conference Board. The choice of the latter variable is mostly dictated by the need to control for other economically relevant variables, including the Consumer Sentiment Index (cf., Carroll, Fuhrer, and Wilcox, 1994). The definition and subsequent collection of *ACSI* data is a fairly recent endeavor started at the University of Michigan. Nonetheless, it has gained popularity and is used nationwide. Stylized variants of the *ACSI* have been developed for China and India. Here our focus is on assessing the value of this measure as it pertains to the U.S. economy. The measurement of *ACSI* is based on a survey instrument administered to over 70,000 consumers per year on a quarterly basis, and associated PLS estimation of measurement and structural equations (Fornell and Bookstein 1982). A detailed description of its measurement is given in Appendix A, its aggregation to the firm-level in Appendix B. In total, 37 quarterly observations of each of the time series (*ACSI, ILI, PCE*) are used.

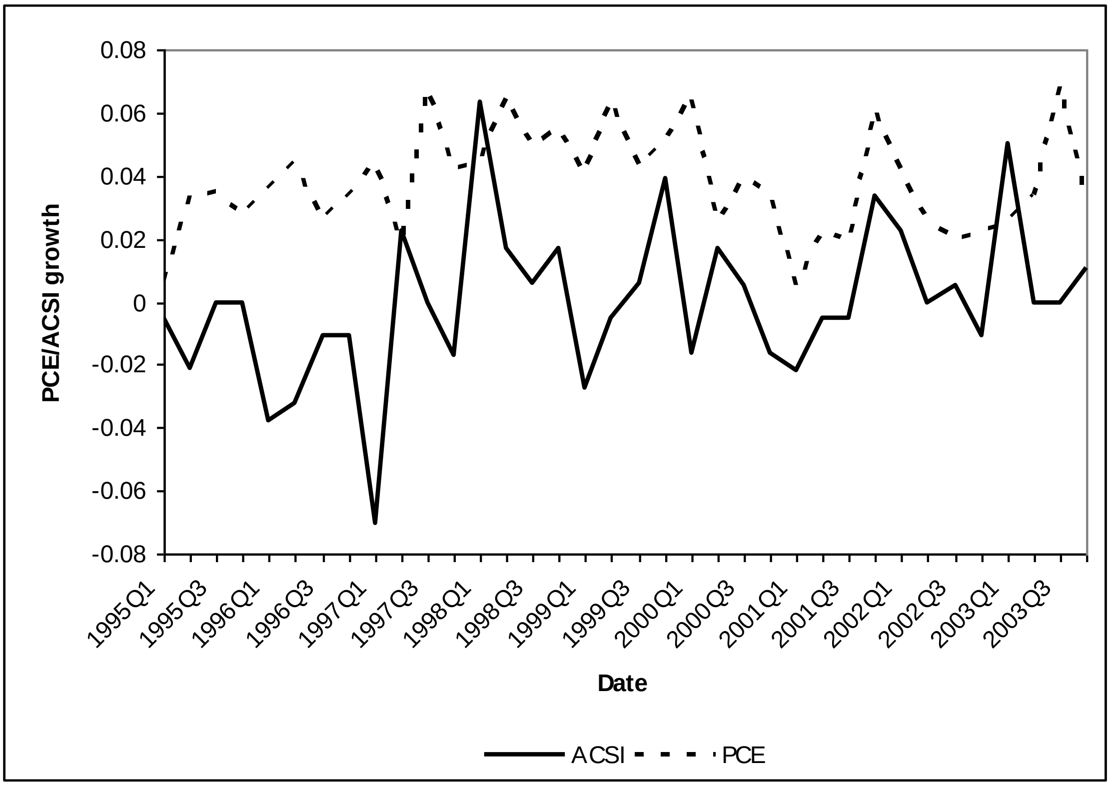
3. METHODOLOGY

Despite its simple structure and intuitive appeal, the estimation of the linkage, if any, from satisfaction growth at time *t-1* to personal consumption growth at time *t* is empirically challenging. From a modeling perspective, given the paucity of data, the type of models one can employ to obtain inference is compromised. Traditional econometric models rely on asymptotic theory, requiring large sample sizes. In contrast, Bayesian methods utilized in this study are better suited to handle small data sets; see, for example, Gelman et al. (2003), and Lancaster (2004). Second, standard parametric methods require specific assumptions about the distributional form of the error term in equation (1) below, which may not always reflect true properties of the data at hand and, as a consequence, may provide biased estimates.[1] In contrast, nonparametric specification of the error term relaxes such distributional assumptions. Finally, as can be seen from Figure 1, both *PCE* and *ACSI* exhibit somewhat similar behavior over time and they both exhibit considerable variation. Estimating the relationship between these two variables could therefore benefit from modeling the variance of the time series via a mean-variance regression that allows for *parameter uncertainty* (where the mean and variance regression parameters are treated as random realizations from a probability model).[2] Hence, in the face of few observations, potential non-normality of the error term, and considerable volatility, we develop a Bayesian semiparametric approach that accommodates both parameter and distributional uncertainty, and is well suited for small sample sizes.

[1] Comparative analyses of the data indicate that the small sample properties of Bayesian estimates are superior to those of OLS. The properties are better the farther the underlying error distribution departs from normality. In addition, the normality assumption required under OLS produces significantly higher in-sample and out-of-sample root mean square errors. Detailed results are available upon request.

[2] By the phrase "mean-variance regression", we imply that both the expected value of the dependent variable and the variance of the error term in the regression are modeled via inter-connected regressions.

Figure 1. Quarterly Time-Series of the *PCE* and *ACSI* Growth for the Period 1995Q1-2003Q4



To begin the formal development of our model, we assume:

$$y_t = \mu_t + e_t, \quad t = 1,\dots,n, \tag{1}$$

where $y_t = \Delta_t\{PCE\}$ is the dependent variable, with $\Delta_t\{w\} = \frac{w_t - w_{t-1}}{w_{t-1}}$ denoting growth in w from t-1 to t, μ_t is the mean of the process and the e_t are independent and identically distributed (iid) error terms. We assume that $E(e_t) = 0$; the e_t are symmetric about 0; and $var(e_t) = \sigma_t^2$.

The mean, μ_t, and the volatility, σ_t^2, are modeled so that they depend on regressors. The class of models in equation (1) where both μ and σ are modeled is very useful in the *PCE-ACSI* context because it allows the mean and volatility of *PCE* (and other economic indicators) to change over time. We specify the mean and variance processes by assuming that beyond the information in the *ILI*, the previous time period's aggregate consumer satisfaction growth affects the current mean *PCE* growth:

$$\mu_t = \beta_0 + \sum_{k=1}^{K} \beta_k x_{kt}, \tag{2}$$

Where $x_{i1} = \Delta_{t-1}\{ACSI\}$ and $x_{i2} = \Delta_{t-1}\{ILI\}$ are *ACSI* and *ILI* growth rates. The β_k are unknown parameters to be estimated. We consider the variance process:

$$\sigma_t = exp\left(\theta_0 + \sum_{l=1}^{L} \theta_l z_{lt}\right), \tag{3}$$

where the $\{z_{lt}\}$ are observed predictor variables affecting the variance process up to and including time *t*, and θ_l are unknown parameters to be estimated. In the empirical analysis, we take $z_t = \Delta_t\{PCE\}$ the one-quarter lagged squared value of y_t as a regressor. That is, the model adapts to changes in volatility as a function of its own past values.

We can write the model in a different way using what is known as a scale mixture of uniform representation, originally proposed by Feller (1971). The reasons for doing this are: (i) broader classes of models that deviate from the normal family are made possible; and (ii) Bayesian implementation is highly simplified because the resulting model lends itself to an easy to implement Markov chain Monte Carlo (MCMC) scheme. Introduce the latent variable $u=(u_1,....u_n)$, and consider the model[3]

$$y_t \mid u_t = \mu_t + \tau_t \sqrt{u_t}, \mathrm{t}=1,........\mathrm{T} \tag{3}$$

where the τ_i are iid from the uniform distribution on (-1,+1), and the u_i are iid from some distribution *F* defined on $(0,\infty)$.[4] For the model given in (3), it can be shown that marginally, for each *i*, y_i is symmetric about its mean, while if $E(u_i) = 3\sigma^2$ then $\mathrm{var}(y_i) = \sigma^2$. Letting *y* denote the observed data with unknown mean μ, Feller's formulation allows us to write the regression model as the following scale mixture model:

$$[y \mid u] \sim U(\mu - u, \mu + u),$$
$$u \sim F, \tag{4}$$

for some distribution function *F* with support on $(0,\infty)$. The distribution of the error term in equation (1) is thus assumed to be a realization of a random process. Since our focus is on providing a flexible distributional form for the error term, we model *F* nonparametrically. The most well known prior distribution on *F* is the Dirichlet process introduced by Ferguson (1973).[5] $F\sim Dir(c, F_0)$ means, *F* is assigned a Dirichlet process prior with mean F_0 and scale

[3] Throughout, we use the following notations. *U* denotes the uniform distribution; "*u~f*" should be read as "*u* has density *f*"; and [*A*|*B*] denotes the conditional distribution of *A* given *B*.

[4] The square root of *u* formulation is convenient from a modeling perspective. In particular, we can express higher moments for *Y* in terms of lower moments of *U*; indeed, taking *u* (instead of its square root) would require the first four moments of *U* to model the first two moments of *Y*.

[5] The formal definition of the Dirichlet process is stated in Appendix 2.

parameter *c*. *c* is a measure of strength of belief in your prior guess at the mean. Note, as an example, one could center the location parameter, F_0, around the family of normal distributions, which is what we do in the analysis of the *ACSI* data. We use the Dirichlet process for two reasons: (i) the theoretical properties of the process are very appealing (see Ferguson, 1973) and; (ii) implementing the overall model is highly simplified; see MacEachern (1998) who demonstrates a substantial reduction in computational burden. When sample sizes are small, inference is based primarily on the centering family, while, with large samples, inference will be based more on the empirical distribution function of the data; see, Gelman et al. (2003).

Now consider the observed sequence $Y_1, Y_2, \ldots, Y_T$ in which the conditional density of the data based on its past values is unimodal and symmetric with the mean and variance depending on the past. We have the following hierarchical modeling framework.

$$[Y_t \mid F_{t-1}] \sim U\left(\mu_{t-1} - \sigma_{t-1}\sqrt{U_t}, \mu_{t-1} + \sigma_{t-1}\sqrt{U_t}\right)$$

$$u_1 \ldots\ldots u_t \sim F \qquad (5)$$

Since $\sigma > 0$ is the volatility parameter, we have a scale-mixture-of-uniforms representation of the observed data conditioned on past values of the mean and volatility. As described above, we take *F* to be based on a Dirichlet process prior. As *F* ranges over all distribution functions, the density of *Y* ranges over all unimodal and symmetric density functions. Consequently, with flexible *F*, the above model can capture very wide ranges of kurtosis in the observed data, unlike the normal errors regression framework.

We assign prior distributions to each of the β_k, and θ_l which, without loss of generality, are assumed to be independent normal distributions with zero means and variances ψ_k^2. The mean-variance regression coupled with the relaxation of distributional assumptions results in a semi-parametric model. In addition to parameter uncertainty, this model also accommodates *distributional uncertainty* (which leads to inferences of superior quality), as described in a collection of papers edited by Dey, Mueller and Sinha (1998). Equation (5) points to an MCMC scheme that one can implement to obtain all posterior and predictive distributions of interest. The MCMC details for our model are presented in Appendix C.

A key output from the MCMC algorithm is predictive distributions from the model described by equations (1)-(3). The capability of obtaining predictive distributions for the dependent variable even with a modest sample size is a desirable consequence of the Bayesian estimation approach.

4. RESULTS

We obtain: (a) The summary statistics of the posterior distribution for the coefficient, β_1, of consumption utility appearing in the mean regression; (b) The summary statistics of the posterior distribution for the coefficient, θ_1, of consumption utility appearing in the variance regression; and (c) The predictive distribution and its summary statistics for a single holdout sample. For the purpose of validating the predictive aspect of our model, the last data point (2003Q4) is left out from the estimation; i.e., it serves as a holdout sample. Since the sample size is small, it is not possible to hold out a larger subset.

Table 1 summarizes the information for the parameters of the mean and variance regressions; the mean and standard deviation of the predictive distribution; and the one-tail probability that the regression coefficient, β_1, in the mean regression is greater than zero. The last statistic is valuable because it provides evidence as to whether or not the independent variable is useful. In traditional statistical terminology, this is somewhat equivalent to a hypothesis test on the usefulness of the regression coefficient. It is clear that the *ACSI* coefficient, β_1, is non-zero since most of its mass is concentrated away from zero. This result is invariant to the inclusion of the Index of Leading Indicators (*ILI*). As shown in Table 1, the estimated coefficient relating the lagged change in *ACSI* to the change in spending is 0.22 with a standard error of 0.11. The probability that this coefficient is greater than 0 equals 0.97, implying that changes in *ACSI* are associated with future changes in *PCE*.

Table 1. Summary of Parameter Estimates:
Posterior Means and Standard Errors (in parentheses)

PARAMETER	VALUE
β_1	**0.215 (0.112)**
$P(\beta_1 > 0)$	**0.971**
θ_1	**-0.115 (0.996)**
μ (True Value)	**3.94% [3.25%]**

The mode of the posterior distribution of the coefficient θ_1 from the variance regression appears to be at zero, but there is still a substantial positive probability (0.452) that it exceeds zero. Thus, from the analysis there is limited evidence that higher levels of change in consumer satisfaction increase the volatility of spending growth, but including the variance regression still mitigates the possible effect of volatility on the parameters of the mean regression.

The kurtosis of the predictive distribution of *PCE* growth for the hold-out observation 2003Q4 is greater than the kurtosis of the normal distribution by 0.335. Thus, by using a nonparametric component to model the error term, a more accurate description of the time series is obtained. The mean of the predictive distribution is 3.94 %, which is fairly close to the actual value of 3.25 %. A 95 % simulation based credible interval for this prediction is (1.4 %; 6.55 %), which gives confidence in the model estimated.

5. DISCUSSION

These findings reveal that consumer satisfaction affects consumer spending growth. As in most observational studies, causality of the ACSI-GDP relationship has not been proven. However, the relationship was predicted from theoretical considerations, the inclusion of lagged variables ensures temporal precedence of the satisfaction effect, and other economically relevant variables were controlled for through the inclusion of the Consumer Sentiment Index. Thus, the results provide an initial supportive answer to the main question: does aggregate household satisfaction predict consumer spending? Satisfaction was found to have predictive power over and beyond the Consumer Sentiment Index (which measures willingness to spend); this is Katona's (1979) central motivator of spending behavior. The results highlight that economic growth derives from successful buyer-seller exchanges. If the outcomes are positive for both parties, each will be motivated to repeat the experience. That is, the impact of the outcome may not only shift consumer preference from one vendor to another, it may also affect the marginal propensity to consume.

The key for maintaining any ongoing buyer-seller relationship lies in the satisfaction of the buyer; the market will make sure that the seller is compensated or penalized accordingly. In the aggregate, the results of economic exchanges created by satisfied consumers are being recorded in GDP accounts. If this interpretation of the empirical results is indeed valid, the implication is that improving the conditions leading to positive buyer-seller evaluations, regardless of consumers' readiness to spend, would stimulate economic growth. A potentially effective means for stimulating economic growth may thus lie outside the current scope of neoclassical and endogenous economic models. Since the satisfaction of a customer is a consequence of exchanges, it follows that economic growth benefits from better buyer-seller transactions. If buyers made better purchase decisions, their satisfaction would be improved. If sellers put more efforts into better customer selection, employee training and customer service, consumer satisfaction would likely benefit. Rather than attempting to boost consumer spending by providing additional means to spend (e.g., after tax income, productivity growth, and lower prices), economic growth might be stimulated by going to the source of value creation in the buyer-seller exchange, namely, the satisfaction of the buyer. Next to focusing on consumers' willingness to spend, this would suggest attending to the conditions under which buyers and sellers become better partners, such as ensuring availability of consumer choice, developing adequate consumer information, and allowing investments in customer service to be capitalized.

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Appendix A. Measurement of ACSI

The *ACSI* comprises a series of equations including both unobservable variables and their observable indicators. Expectations and customers' experienced quality and value are specified to affect their satisfaction, which, in turn, impacts propensity to voice (complain) and repurchase. These latent variables measured in the *ACSI* are related as follows:

$$\begin{bmatrix} \eta_1 \\ \eta_2 \\ \eta_3 \\ \eta_4 \\ \eta_5 \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ \beta_{21} & 0 & 0 & 0 & 0 \\ \beta_{31} & \beta_{32} & 0 & 0 & 0 \\ 0 & 0 & \beta_{43} & 0 & 0 \\ 0 & 0 & \beta_{53} & \beta_{54} & 0 \end{bmatrix} \begin{bmatrix} \eta_1 \\ \eta_2 \\ \eta_3 \\ \eta_4 \\ \eta_5 \end{bmatrix} + \begin{bmatrix} \gamma_{11} \\ \gamma_{21} \\ \gamma_{31} \\ 0 \\ 0 \end{bmatrix} \xi + \begin{bmatrix} \xi_1 \\ \xi_2 \\ \xi_3 \\ \xi_4 \\ \xi_5 \end{bmatrix}, \qquad \text{(A.1)}$$

where ξ denotes expectations, and η_1 to η_5 represent "experienced" quality, "perceived" value, *ACSI*, voice and customer "loyalty". The corresponding measurement equations in the model are:

$$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} \lambda_{11} \\ \lambda_{21} \\ \lambda_{31} \end{bmatrix} \xi + \begin{bmatrix} \delta_1 \\ \delta_2 \\ \delta_3 \end{bmatrix}, \qquad \text{(A.2)}$$

$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \\ y_5 \\ y_6 \\ y_7 \\ y_8 \\ y_9 \\ y_{10} \\ y_{11} \end{bmatrix} = \begin{bmatrix} \lambda_{11} & 0 & 0 & 0 & 0 \\ \lambda_{21} & 0 & 0 & 0 & 0 \\ \lambda_{31} & 0 & 0 & 0 & 0 \\ 0 & \lambda_{12} & 0 & 0 & 0 \\ 0 & \lambda_{22} & 0 & 0 & 0 \\ 0 & 0 & \lambda_{13} & 0 & 0 \\ 0 & 0 & \lambda_{23} & 0 & 0 \\ 0 & 0 & \lambda_{33} & 0 & 0 \\ 0 & 0 & 0 & \lambda_{14} & 0 \\ 0 & 0 & 0 & 0 & \lambda_{15} \\ 0 & 0 & 0 & 0 & \lambda_{25} \end{bmatrix} \begin{bmatrix} \eta_1 \\ \eta_2 \\ \eta_3 \\ \eta_4 \\ \eta_5 \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \varepsilon_4 \\ \varepsilon_5 \\ \varepsilon_6 \\ \varepsilon_7 \\ \varepsilon_8 \\ \varepsilon_9 \\ \varepsilon_{10} \\ \varepsilon_{11} \end{bmatrix}, \qquad \text{(A.3)}$$

where *x* and *y* are vectors of manifest variables from the *ACSI* survey, and further defined in Fornell et al. (1996). By implication from Wold's PLS estimation (Fornell and Bookstein, 1982), the noise or measurement error has the properties: $E[\varepsilon] = E[\delta] = 0$, $E[\eta\varepsilon'] = E[\xi\delta'] = 0$.

Appendix B. Aggregation of ACSI per Firm

The satisfaction scores per firm are aggregated as follows. Let

$$I_{ist} = \sum_{f}^{F} \frac{S_{fist} I_{fist}}{\sum_{f}^{F} S_{fist}} \quad , \tag{B.1}$$

$$I_{st} = \sum_{i}^{I} \frac{S_{ist} I_{ist}}{\sum_{i}^{I} S_{ist}} , \tag{B.2}$$

where

I_{ist} = Index for industry *i* in sector *s* at time *t*,

I_{st} = Index for sector *s* at time *t*,

S_{fist} = Sales by firm *f*, industry *i*, sector *s* at time *t*,

I_{fist} = Index for firm *f*, industry *i*, sector *s* at time *t*,

$S_{ist} = \sum_{f}^{F} S_{fist}$ = Total Sales for industry *i* at time *t*, and

$S_{st} = \sum_{i}^{I} S_{ist}$ = Total Sales for sector *s* at time *t*.

The index is updated quarterly. For each quarter, new scores are estimated for one or more sectors with total replacement of all data annually. The National Index is then comprised of the most recent estimate for each sector

$$(National\ Index)_t = I_t = \sum_{t=T-3}^{T} \sum_{s}^{S} \frac{S_{st} I_{st}}{\sum_{t=T-3}^{T} \sum_{s}^{S} S_{st}} , \tag{B.3}$$

where $I_{st}=0$ for all *t* in which the index for a sector is not estimated, and $I_{st}=I_{st}$ for all quarters in which an index is estimated.

Appendix C. The Markov Chain Monte Carlo (MCMC) Algorithm

The following describes the various priors used in the empirical analysis. Where necessary, a conjugate hyper-prior is used; see, for example, Walker et al. (1999). Non-conjugate prior distributions can also readily be employed if needed; for details, see MacEachern (1998); Mira et al. (2001).

In our estimation we choose the Dirichlet process of Ferguson (1973) as a nonparametric prior. To define the process, we first introduce the concept of the Dirichlet distribution. Let $\tilde{Z}_1,\ldots,\tilde{Z}_k$ be independent random variables with $\tilde{Z}_j$ having a Gamma distribution with shape parameter $c_j \geq 0$ and scale parameter 1, for $j=1, 2,\ldots,k$. Let $c_j > 0$ for some j. The Dirichlet distribution with parameter $(c_1, c_2, \ldots, c_k)$, denoted by $D(c_1, c_2, \ldots, c_k)$, is defined as the distribution of $(\tilde{\theta}_1, \tilde{\theta}_2, \ldots, \tilde{\theta}_n)$, where $\tilde{\theta}_j = \tilde{Z}_j / \sum_{i=1}^{k} \tilde{Z}_i$, $j = 1, 2, \ldots, k$. To define the Dirichlet process itself, let c be a finite nonnull measure (nonnegative and finitely additive) on (R^m, B). P is a Dirichlet process with parameter c, denoted by $P \in D(c)$, if for every finite measurable partition $\{B_1,\ldots, B_n\}$ of R^m (i.e., the B_i are measurable, disjoint and $\bigcup_{i=1}^{n} B_i = R^m$), the random vector $(P(B_1), P(B_2), \ldots, P(B_n))$ has a Dirichlet distribution with parameter $(c(B_1), c(B_2), \ldots, c(B_n))$.

Based on Ferguson (1973), the scale parameter of the Dirichlet process, c, is assigned a Gamma (a, b) hyper-prior distribution. The location parameter is the prior guess at F_0. In this paper, for illustrative purposes, we center the transition density on the family of normal distributions.

All our prior settings were chosen to reflect vague prior knowledge, a so-called objective prior setting. Denoting π to be a prior distribution, $\pi(\beta_0) = N(0,5)$, $\pi(\beta_1) = N(0,5)$ in the mean regression; and $\pi(\theta_0) = N(0,5)$, $\pi(\theta_1) = N(0,5)$ in the variance regression. We take $\pi(c)$ the scale parameter of the Dirichlet process, to be Gamma (a, b) with $a = b = 0.01$. Since we are centering the transition density on the normal distribution, we take the location F_0 to be a Gamma $(3/2, 1/2)$ in the uniform scale mixture.

Since there is no closed-form description for the posterior and predictive distributions, we use a Gibbs sampler. The Gibbs sampler is an MCMC method for sampling from conditional distributions, which, in the limit, induces samples from the required posterior marginal distributions of interest (Smith and Roberts, 1993; Mira, et al., 2001). Hence, the first requirement in implementing a Gibbs sampler is to obtain the conditional distributions, up to proportionality, of the random variables of interest.

For the model in this paper, the following full conditional densities have to be sampled,

1. $[u_i \mid \text{everything else}]$, $i = 1, \ldots\ldots., N$;
2. $[\theta_l \mid \text{everything else}]$, $l = 1,\ldots, L$;
3. $[\beta_k \mid \text{everything else}]$, $k = 1, \ldots\ldots., K$;
4. $[c \mid \text{everything else}]$.

N equals the number of data points in the sample and L and K are the number of independent variables in the mean and variance regressions, respectively. The Gibbs sampler, indexed by superscript (s), successively samples from the following full conditional distributions.

<u>1. $[u_i|\ldots..]$</u>

The full conditional here is given by

$$u_i^{-1/2} I(u_i > r_i^2 / \sigma^{2(s-1)}) p(u_i \mid u_{-i}), \tag{C.1}$$

$$[u_i \mid u_{-i}] \propto c^{(s-1)} f(u_i) + \sum_{j \neq i} \delta_{u_j}(u_i), \tag{C.2}$$

where δ_u is the point mass 1 at u, and u_{-i} denotes all values of u except for u_i. Recall that $f(u) \propto u^{-1/2} \exp(-u/2)$. Consequently, we either sample u_i from a truncated exponential distribution or take u_i to be u_j, for those $u_j > r_i^2 / \sigma^{2(s-1)}$, according to probabilities, which are straightforward to compute. In fact,

$$u_i^{(s)} = \begin{cases} \sim f^*(u) & \text{with probability} \quad \propto \tau \exp(-a/2) \\ = u_j & \text{with probability} \quad \propto 1/\sqrt{u_j} \end{cases} \tag{C.3}$$

where $\tau = c^{(s-1)} / (4\sqrt{\pi})$, $a = r_i^2 / \sigma^{2(s-1)}$ and $f^*(u) = 0.5 \exp\left\{-\left(u^{(s-1)} - a\right)/2\right\} I(u^{(s-1)} > a)$.

<u>2. $[\theta_l|\ldots..]$</u>

Define

$$\lambda_t = \frac{0.5\ln\left(r_t - \sum_{j=1}^{K}\beta_j^{(s-1)}Z_{jt}\right)^2}{u_t^{(s)}} - \sum_{j\neq l}\theta_j^{(s-1)}W_{jt} \tag{C.4}$$

and $\pi(.)$ to be a prior distribution function for θ, so

$$\left[\theta_l^{(s)} \mid \ldots\right] \propto \pi(\theta_l) I\left(\theta_l \in \left[\max_{W_{lt}<0}\{\lambda_t / W_{lt}\}, \min_{W_{lt}>0}\{\lambda_t / W_{lt}\}\right]\right) \tag{C.5}$$

If $W_{lt} > 0$ for all t then

$$\max_{W_{lt}<0}\{\lambda_t / W_{lt}\} = -\infty \tag{C.6}$$

and if $W_{lt}<0$ for all t then

$$\min_{W_{lt}>0}\{\lambda_t / W_{lt}\} = \infty \tag{C.7}$$

3. [β_k|…]

Define

$$\lambda_t = r_t - \sigma^{(s-1)}\sqrt{u_i^{(s)}} - \sum_{j\neq k}\beta_j^{(s-1)}Z_{jt}, \tag{C.8}$$

where

$$\sigma^{(s)} = \exp\left(\sum_{j=1}^{L}\theta_j^{(s)}W_{jt}\right) \tag{C.9}$$

and $\pi(.)$ to be a prior distribution function for θ, so

$$\left[\beta_k^{(s)} \mid \ldots.\right] \propto \pi(\beta_k) I\left(\beta_k \in \left[\max_{Z_{kt}<0}\{\lambda_t / Z_{kt}\}, \min_{Z_{kt}>0}\{\lambda_t / Z_{kt}\}\right]\right) \tag{C.10}$$

If $Z_{kt}>0$ for all t then

$$\max_{Z_{kt}<0}\{\lambda_t / Z_{kt}\} = -\infty \tag{C.11}$$

and if $Z_{kt}<0$ for all t then

$$\min_{Z_{kt}>0}\{\lambda_t / Z_{kt}\} = \infty \tag{C.12}$$

4. [c|…]

The sampling for c proceeds as follows. In the first step, sample from the beta distribution for the new latent parameter $\eta \in (0,1)$;

$$[\eta \mid c, k] \sim beta\left(c^{(s-1)} + 1, N\right) \tag{C.13}$$

Then c is sampled from the mixture of gamma distributions, where the weights are defined as below,

$$\left(c^{(s)} \mid \eta, k\right) \sim \pi_{\eta} Ga\left(k+a, b-Im\eta\right)+(1-\pi_{\eta})Ga\left(a+k-1, b-Im\eta\right) \tag{C.14}$$

Here *Ga (a,b)* is the prior distribution for c with a=b=0.01; and π_η is the solution of the equation

$$\pi_{\eta}/(1-\pi_{\eta})=(a+k-1)/N(b-Im\eta) \tag{C.15}$$

Recall that a strength of the Bayesian approach is that one can readily obtain the predictive distribution of the dependent variable. In order to construct the predictive distribution, we extend the Gibbs sampler above. For the predictions for period *N+1*, we would sample the following components

$$Y_{N+1} \sim U_n\left(\mu_N - \sigma_N\sqrt{u_{N+1}}, \mu_N + \sigma_N\sqrt{u_{N+1}}\right) \tag{C.16}$$

where μ_N is defined as

$$\mu_N = e^{\beta Z_N} \tag{C.17}$$

and σ_N is defined as

$$\sigma_N = e^{\theta W_N} \tag{C.18}$$

and Z_N is the value of the covariate at the time of prediction while u_{N+1} is sampled as below,

$$u_{N+1} = \begin{cases} \sim f(u) & \text{with probability} \propto c \\ = u_j & \text{with probability} \propto 1 \end{cases}$$

Here *f(u)* is *Gamma* (1.5, 0.5). A Y_{N+1} can be obtained from each iteration of the Gibbs sampler, using the current (c,β). The above algorithm is extended until the predicted value of Y_T is obtained by taking a simple average of the Y_Ts from each iteration of the Gibbs sampler.

Armed with the prior choices described above, and using the Gibbs sampler, samples were drawn from the full conditional distributions. Specifically, our Gibbs sampler involves 100,000 Monte Carlo iterations. Using well-known convergence diagnostics (Smith and Roberts, 1993), having “burned-in” the first 80,000 iterates, the remaining sampled variates were used for inference.