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# Estimating Demand Elasticities in Non-Stationary Panels: The Case of Hawaii Tourism Industry

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# Estimating Demand Elasticities in Non-Stationary Panels: The Case of Hawaii Tourism

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**Abstract**

Tourism demand elasticities are central to marketing, forecasting and policy work, but the wide array of occasionally counterintuitive estimates produced by existing empirical studies implies that some of those results may be inaccurate. To improve the precision of estimates, it is natural to turn to the richness of panel data. However, panel estimation using non-stationary data requires careful attention to the likely presence of common shocks shared across the underlying macroeconomic variables and across regions. Several recently developed econometric tools for panel data analysis attempt to deal with such cross-sectional dependence. We apply the estimator of Pesaran (2006) and Kapetinos, Pesaran and Yamagata (2010) to obtain tourism demand elasticities in non-stationary heterogeneous dynamic panels subject to common factors. We study the extent to which tourism arrivals from the US Mainland to Hawaii are driven by fundamentals such as real personal income and the cost of the trip, and we find that neglecting cross-sectional dependence in the data leads to spurious results.

*JEL classifications: C23, C51, L83, R41*

*Keywords:* Panel Cointegration, Cross-Sectional Dependence, Tourism Demand, Hawaii.

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# 1 Introduction

The dramatic growth in tourism over the past several decades has led to an extensive literature which seeks to explain and forecast tourism flows. Following a wide variety of empirical methods applied across different countries and time periods, researchers have produced an even wider array of estimates for the demand elasticities central to marketing, forecasting and policy work. While the income elasticity of tourism demand is generally expected to lie between one and two, Crouch (1995, 1996) found that nearly 5% of estimates from 80 international studies were negative. Analyzing 30 years of international tourism demand studies, Witt and Witt (1995) found income elasticity estimates ranging from 0.4 to 6.6 with a median value of 2.4. Although an "inferior" tourism destination could explain a negative income elasticity, and an elasticity of less than 1 might be explained by some "necessary" short-haul international trips, such as those from the US to Canada, the large variation in estimates calls into question their validity and limits their usefulness to decision-makers. Estimates of price elasticities fare about the same. Witt and Witt (1995) found estimates ranging from -0.05 to -1.5, and Crouch (1995, 1996) found about 29% of the estimates were positive. Finally, these studies found transportation price elasticity estimates ranging from 0.11 to -4.3. Crouch (1996) investigated a number of potential causes of such disparate results, and noted that model specification played an important role. We suspect that the wide range of elasticity estimates arise for a variety of reasons ranging from small samples with limited information in time series models to the use of panel estimation techniques that do not adequately deal with important characteristics of panel data.

Early tourism demand studies focused almost exclusively on estimation of single equation models using time series data for a single origin-destination pair (Li et al., 2005; Witt and Witt, 1995). But the limited data available for estimation has likely contributed to imprecise estimates of demand elasticities. Fortunately, it may be possible to obtain better estimates of the parameters of interest by taking advantage of the variation in both the temporal and cross-sectional dimensions of panel data sets. This point has not been lost on the tourism literature, and as econometric tools have advanced, a trend to exploit the richness of panel data has emerged (Seetaram and Petit, 2012; Song and Li, 2008).

While early panel studies ignored issues arising from nonstationarity and potential cointegration, the tourism literature has now begun to address such issues. Among others, Seetanah et al. (2010) estimated a static model of demand for South African tourism using Fully Modified OLS developed by Pedroni (2001). Using the same technique, Lee and Chang (2008) investigated the long-run co-movements and causal relationships between tourism development and economic growth. Falk (2010) applied the dynamic heterogeneous panel technique of Pesaran et al. (1999) to estimate the effects of snow fall on winter tourism in Austria.

One common thread running through this nascent literature is the reliance on the assumption of cross-sectional independence, or that each unit contributes entirely new information to the dataset. Yet, cross-sectional units are almost certainly influenced by national or global shocks such as business cycles, technological innovations, terrorism events, oil crises or national fiscal and monetary policies. In fact, a large empirical macro and macro-finance literature (see Stock and Watson, 1989, 1998) and results presented here for Hawaii's tourism show that cross-sectional dependence is very common. And, neglecting cross-sectional dependence results in substantial bias of conventional panel estimators (Kapetanios et al., 2010).

A novel solution to this problem is to model cross-sectional dependence using a factor structure. Some tourism demand studies have taken the approach of including observed proxies for unobserved common factors. For example, Nelson et al. (2011) used oil prices, indicator variables for the effects of the 9/11 terrorist attacks, and a nonlinear time trend capturing the overall slow-down of tourism demand during recessions. Such proxy variables may be effective in mitigating the effects of cross-sectional dependence, but their choice involves judgement on the part of the researcher, and it is unclear whether they are adequate to capture all sources of common shocks. Alternatively, unobserved dynamic common factors can be approximated using the methods proposed by Bai et al. (2009), Pesaran (2006), or Kapetanios et al. (2010). These approaches have the benefit that they do not require selection of a set of observed proxies.

We estimate tourism demand elasticities from a panel of visitor arrivals to Hawaii from 48 US states over 19 years using the common correlated effects (CCE) estimator of Pesaran (2006) and Kapetanios et al. (2010). This technique offers many advantages. First, the CCE estimator allows us to address the possibility of cross-sectional dependence caused by common factors. Second, it does not require ex ante information about the unobserved factors, allows them to contain unit roots, and to be correlated with the regressors. Finally, the CCE estimator offers good finite sample properties (Kapetanios et al., 2010; Westerlund and Urbain, 2011), and is relatively simple to implement.

The rest of this paper is organized as follows: in Section 2 we outline our tourism demand model; in Section 2 we describe recently developed econometric techniques that deal with cross-sectional dependence in panels; in Section 3 we apply these techniques to estimate demand elasticities for Hawaii tourism; and Section 4 concludes.

# 2 Tourism Demand Model and Econometric Modeling

The demand for aggregate tourism flows from origin $i$ to destination $j$ can be written as

$$D_{ij} = f(Y_i, P_i, P_j, P_s) \ , \tag{1}$$

where $D_{ij}$ is a measure of tourism demand in destination $j$ by consumers from origin $i$; $Y_i$ is the level of income at origin $i$; $P_i$ is the price of other goods and services at origin $i$; $P_j$ is the price of tourism goods and services at destination $j$; $P_s$ is the price of tourism products at competing destinations (Bonham et al., 2009). Assuming homogeneity, demand can be written as a function of real income, and relative prices

$$D_{ij} = f\left(\frac{Y_i}{P_i}, \frac{P_j}{P_i}, \frac{P_s}{P_i}\right) \ . \tag{2}$$

If travel to destination $j$ is assumed to be competing with short distance trips near the origin, the tourism demand model can be simplified to

$$D_{ij} = f\left(\frac{Y_i}{P_i}, \frac{P_j}{P_i}\right) \ . \tag{3}$$

For tourism models explaining aggregate tourism flows to a single destination (inbound modeling), the most popular measure of tourism demand is the number of visitor arrivals (Li et al., 2005; Song and Li, 2008). Proxies for demand determinants include various measures of income and relative prices. Witt and Witt (1995) recommend using personal income to predict holiday travel, and a more general income measure, such as national income, to predict business travel. In addition, they suggest that the price measures should include both the cost of travel to the destination and cost of living at the destination.

The long-run relation consistent with the theoretical tourism demand model (3) can be written in the following log-linear form

$$y_{it} = \alpha_i + \boldsymbol{\beta}_i' \boldsymbol{x}_{it} + u_{it} \ , \ i = 1, 2, \ldots, N \ , \ t = 1, 2, \ldots, T \ , \tag{4}$$

where $y_{it} = \log(D_{ij,t})$, $\boldsymbol{x}_{it} = \left(\log\left(\frac{Y_{i,t}}{P_{i,t}}\right), \log\left(\frac{P_{j,t}}{P_{i,t}}\right)\right)'$. The coefficients $\boldsymbol{\beta}_i$ represent the elasticites of demand with respect to the regressors $\boldsymbol{x}_{it}$. The dynamics and the common unobserved factors are modeled in the error terms $u_{it}$. In particular, $u_{it}$ is assumed to have the following structure

$$u_{it} = \gamma_i' \boldsymbol{f}_t + \epsilon_{it} \ , \ i = 1, 2, \ldots, N \ , \ t = 1, 2, \ldots, T \ , \tag{5}$$

in which $\boldsymbol{f}_t$ is an $m \times 1$ vector of unobserved common effects, and $\epsilon_{it}$ are the individual-specific (idiosyncratic) errors assumed to be distributed independently of $\boldsymbol{x}_{it}$ and $\boldsymbol{f}_t$. However, the $\epsilon_{it}$ are allowed to be weakly dependent across $i$, and serially correlated over time.

The CCE estimator asymptotically eliminates cross-sectional dependencies from the errors, $u_{it}$, and is based on the assumption that the $k \times 1$ vector $\boldsymbol{x}_{it}$ is generated as

$$\boldsymbol{x}_{it} = \boldsymbol{a}_i + \boldsymbol{\Gamma}_i' \boldsymbol{f}_t + \boldsymbol{v}_{it} \ , \ i = 1, 2, \ldots, N \ , \ t = 1, 2, \ldots, T, \tag{6}$$

where $\boldsymbol{a}_i$ is a $k \times 1$ vector of individual effects, and $\boldsymbol{\Gamma}_i$ is a $m \times k$ factor loading matrix. The idiosyncratic components $\boldsymbol{v}_{it}$ are distributed independently of the common effects and across $i$, but assumed to follow general covariance stationary processes. A valuable feature of the model is that the error term, $u_{it}$, is allowed to be correlated with the regressors, $\boldsymbol{x}_{it}$, through the presence of the factors, $\boldsymbol{f}_t$, in both. Finally, the assumption that $\epsilon_{it}$ (in equation 5) is stationary implies that if $\boldsymbol{f}_t$ contains unit root processes then $y_{it}$, $\boldsymbol{x}_{it}$, and $\boldsymbol{f}_t$ must be cointegrated.

Because the error term, $u_{it}$, contains common factors that are correlated with the regressors, failure to account for this correlation will generally produce biased estimates of the parameters of interest. Pesaran (2006) suggested using cross section averages of $y_{it}$ and $\boldsymbol{x}_{it}$ to deal with the effects of the unobserved factors. His CCE estimator is defined as,

$$\hat{\boldsymbol{\beta}}_{\boldsymbol{i}} = (\boldsymbol{X}_i' \bar{\boldsymbol{M}} \boldsymbol{X}_i)^{-1} \boldsymbol{X}_i' \bar{\boldsymbol{M}} \boldsymbol{y}_i \ , \tag{7}$$

where $\boldsymbol{X}_i = (\boldsymbol{x}_{i1}, \boldsymbol{x}_{i2}, \ldots, \boldsymbol{x}_{iT})'$, $\boldsymbol{y}_i = (y_{i1}, y_{i2}, \ldots, y_{iT})'$, and $\bar{\boldsymbol{M}} = \boldsymbol{I}_T - \bar{\boldsymbol{H}}(\bar{\boldsymbol{H}}'\bar{\boldsymbol{H}})^{-1}\bar{\boldsymbol{H}}'$ with $\bar{\boldsymbol{H}} = (\boldsymbol{\iota}, \bar{\boldsymbol{X}}, \bar{\boldsymbol{y}})$, and $\boldsymbol{\iota}$ is a $T \times 1$ vector of ones. $\bar{\boldsymbol{X}}$ is a $T \times k$ matrix of cross-sectional means of the $k$ regressors, and $\bar{\boldsymbol{y}}$ is a $T \times 1$ vector of cross-sectional means of the dependent variable. While Pesaran (2006) derived the CCE estimator for stationary variables and factors, Kapetanios et al. (2010) proved that the CCE estimators are consistent regardless of whether the common factors, $\boldsymbol{f}_t$, are stationary or non-stationary. In addition, they showed that the CCE estimator of the mean of the slope coefficients is consistent for any number of factors. These two results are important benefits of the CCE estimator: we do not need to know how many common factors exist, whether or not the common factors are stationary, or even provide estimates of the common factors and their loadings. In contrast, Bai et al. (2009) estimate homogenous slope coefficients jointly with common factors using an iterative procedure, but the precision of this approach substantially depends on prior knowledge of the number of unobserved factors. Moreover, Kapetanios et al. (2010) and Westerlund and Urbain (2011) have shown that the CCE estimators have lower bias than those of Bai et al. (2009) even if the true number of factors is known.

The objective of this paper is to obtain the best possible estimates for income, price and travel cost elasticities of demand for Hawaii tourism. For that reason, rather than analyze the unit specific vector of the slope coefficients, $\boldsymbol{\beta}_i$, we focus on the estimation of their average value.[1] The CCE mean group estimator (CCEMG) is a simple average of the individual CCE estimators, $\boldsymbol{\beta}_i$,

$$\hat{\boldsymbol{\beta}}_{CCEMG} = \frac{1}{N}\sum_{i=1}^{N}\hat{\boldsymbol{\beta}}_{\boldsymbol{i}} \ , \tag{8}$$

and its variance is given by

$$\widehat{Var}(\hat{\boldsymbol{\beta}}_{\boldsymbol{CCEMG}}) = \frac{1}{N(N-1)}\sum_{i=1}^{N}(\hat{\boldsymbol{\beta}}_{\boldsymbol{i}} - \hat{\boldsymbol{\beta}}_{\boldsymbol{CCEMG}})(\hat{\boldsymbol{\beta}}_{\boldsymbol{i}} - \hat{\boldsymbol{\beta}}_{\boldsymbol{CCEMG}})' \ . \tag{9}$$

When the slope coefficients, $\boldsymbol{\beta}_i$, are homogeneous, efficiency gains can be achieved by pooling observations over the cross section units. Pesaran (2006) developed such a pooled estimator

$$\hat{\boldsymbol{\beta}}_{CCEP} = (\sum_{i=1}^{N}\boldsymbol{X}_i'\bar{\boldsymbol{M}}\boldsymbol{X}_i)^{-1}\sum_{i=1}^{N}\boldsymbol{X}_i'\bar{\boldsymbol{M}}\boldsymbol{y}_i \ , \tag{10}$$

with variance

$$\widehat{Var}(\hat{\boldsymbol{\beta}}_{\boldsymbol{CCEP}}) = \frac{1}{N}\hat{\boldsymbol{\Psi}}^{\boldsymbol{*-1}}\hat{\boldsymbol{R}}^{*}\hat{\boldsymbol{\Psi}}^{\boldsymbol{*-1}} \ , \tag{11}$$

[1] Assuming a random coefficient model, $\boldsymbol{\beta}_i = \boldsymbol{\beta} + \boldsymbol{w}_i$, where $\boldsymbol{w}_i \sim IID(\boldsymbol{0}, \boldsymbol{V_w})$, the overall demand elasticities are $\boldsymbol{\beta} = E(\boldsymbol{\beta}_i)$.

where

$$\hat{\boldsymbol{\Psi}}^* = \frac{1}{N}\sum_{i=1}^{N}\frac{\boldsymbol{X}_i'\bar{\boldsymbol{M}}\boldsymbol{X}_i}{T}\ , \tag{12}$$

and

$$\hat{\boldsymbol{R}}^* = \frac{1}{N-1}\sum_{i=1}^{N}(\frac{\boldsymbol{X}_i'\bar{\boldsymbol{M}}\boldsymbol{X}_i}{T})(\hat{\boldsymbol{\beta}}_{\boldsymbol{i}} - \hat{\boldsymbol{\beta}}_{\boldsymbol{CCEMG}})(\hat{\boldsymbol{\beta}}_{\boldsymbol{i}} - \hat{\boldsymbol{\beta}}_{\boldsymbol{CCEMG}})'(\frac{\boldsymbol{X}_i'\bar{\boldsymbol{M}}\boldsymbol{X}_i}{T})\ . \tag{13}$$

The CCE estimator of $\boldsymbol{\beta}_{\boldsymbol{i}}$ is equivalent to ordinary least squares applied to an auxiliary regression that is augmented with the cross-sectional means of the variables. The method is based on orthogonal projections of the variables onto their cross-sectional means, so that the $\hat{\boldsymbol{\beta}}_{\boldsymbol{CCEMG}}$ and $\hat{\boldsymbol{\beta}}_{\boldsymbol{CCEP}}$ coefficient estimates capture elasticities after controlling for global trends in the data. Thus, the CCE estimates are computed from idiosyncratic variation in the panels. In contrast, an identical time series model based on aggregate data (without cross-sectional dimension) is similar to a regression equation of cross-sectional means, which contains the global factors and under the assumptions of the CCE model suffers from endogeneity and potentially non-stationary residuals.

In the next section we describe our empirical model and report estimation results.

# 3 Estimating Demand Elasticities for Hawaii

The goal of our study is to estimate demand elasticities for tourism from the U.S. mainland to Hawaii using a panel of visitor arrivals from 48 states spanning 19 years. We use visitor arrivals ($VIS_{it}$) as the measure of tourism demand, and total personal income by state ($Y_{it}$) as our measure of income.[2] We include two price variables in our model: the price of airfare ($PAIR_{it}$) and the price of renting a hotel room ($PRM_t$). Nominal variables are deflated using the consumer price index at the origin ($CPI_{it}$), so that prices enter the model in

[2]Witt and Witt (1995) suggest use of personal income for leisure destinations. The majority (over 70%) of tourists come to Hawaii for holiday.

relative terms. The estimated model may be written as

$$\log VIS_{it} = \alpha_i + \beta_{1i} \log \left( \frac{Y_{it}}{CPI_{it}} \right) + \beta_{2i} \log \left( \frac{PAIR_{it}}{CPI_{it}} \right) + \beta_{3i} \log \left( \frac{PRM_t}{CPI_{it}} \right) + u_{it} \ . \quad (14)$$

## 3.1 Data

Our sample containing 77 periods begins in the first quarter of 1993 and ends in the first quarter of 2012. The sample size is determined by the availability of data on visitor arrivals from the US mainland to Hawaii. These data are from various reports of the Hawaii Department of Business, Economic Development and Tourism, Hawaii Tourism Authority, the Hawaii Visitors and Convention Bureau, and the Hawaii Visitors Bureau. Visitor arrivals data are available monthly for all years except 1995 and 1997, for which we use interpolated annual values. Data for total personal income is from the Bureau of Economic Analysis, and airfares to Hawaii are from the DB1B Market database of the Bureau of Transportation Statistics, which offers a 10% random sample of all domestic trips each quarter. From the available sample, we calculate the median airfare for each state and each quarter. We exclude Delaware and the District of Columbia from our analysis due to the lack of airfare data. The Hawaii statewide average hotel room rate is from Hospitality Advisors LLC. The consumer price index is from the US Bureau of Labor Statistics. Because the CPI is only reported at the metropolitan level, we proxy state consumer prices using the CPI for metropolitan areas within the state. Where a metropolitan area CPI is not available, we use the CPI for the region as a proxy for state consumer prices. The CPI data is reported at a variety of frequencies, and we linearly interpolate the lower frequency series to approximate their values at the highest (monthly) frequency. We aggregate all monthly series to the quarterly frequency and seasonally adjust the data using the X-12 ARIMA method.[3]

To avoid the possible effects of outliers, we follow the procedure suggested by Perron and Rodríguez (2003) to test for and remove additive outliers in all series. As noted above,

[3]Personal income is already seasonally adjusted by the Bureau of Economic Analysis.

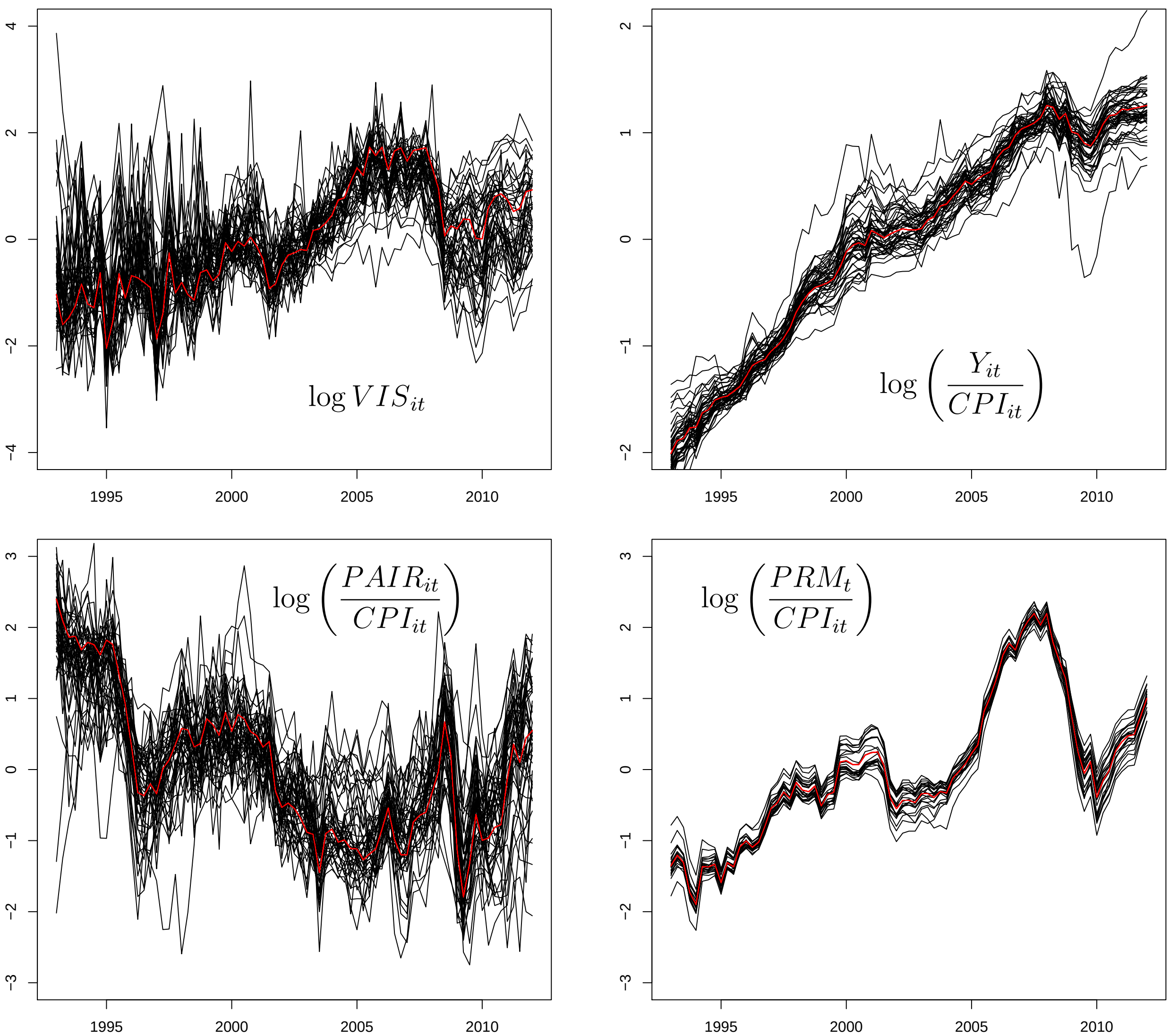


Figure 1: Time plots (1993Q1 - 2012Q1) of standardized logarithms of quarterly visitor arrivals ($VIS_{it}$), real income ($\frac{Y_{it}}{CPI_{it}}$), real airfare ($\frac{PAIR_it}{CPI_{it}}$) and real room rate ($\frac{PRM_t}{CPI_{it}}$) by state of origin. The red line in each graph represents the cross-sectional average of the series.

the CCE estimator produces consistent estimates of the demand elasticities in equation (14) regardless of whether the series are stationary or non-stationary. Nevertheless, we test each variable in equation (14) for unit roots and can not reject the null hypothesis for any of the series. The variables used in the model are plotted in Figure 1. The plotted series are standardized so that all cross-sectional units fit into a single plot. Estimation is carried out without this standardization.

## 3.2 Results

To illustrate the impact of cross-sectional dependence on our parameter estimates, Table 1 compares the CCE estimates and the fully modified ordinary least squares (FMOLS) estimates commonly used in the tourism literature (Seetaram and Petit, 2012). The FMOLS income elasticity estimate is small and the room price elasticity has the wrong sign.

Table 1: Panel Estimates

$$\log VIS_{it} = \alpha_i + \beta_{1i} \log\left(\frac{Y_{it}}{CPI_{it}}\right) + \beta_{2i} \log\left(\frac{PAIR_{it}}{CPI_{it}}\right) + \beta_{3i} \log\left(\frac{PRM_t}{CPI_{it}}\right) + u_{it} \tag{14}$$

| Coefficient | $\beta_1$ | $\beta_2$ | $\beta_3$ | |
|---|---|---|---|---|
| FMOLS | 0.34* | -0.37* | 0.52* | |
| CCE-MG | 1.20* | -0.23* | -1.23* | |
| CCE-P | 1.27* | -0.26* | -1.20* | |

FMOLS Residual Diagnostics

| | $t_{PP}$ | $t_{ADF}$ | $CD$ | $CRMA$ |
|---|---|---|---|---|
| | -6.90* | -4.65* | 68.93* | -1.56 |

CCE Residual Unit Root Test

| | CADF(1) | CADF(2) | CADF(3) | CADF(4) |
|---|---|---|---|---|
| CCE-MG | -24.72* | -17.72* | -16.82* | -10.64* |
| CCE-P | -25.95* | -19.73* | -19.42* | -14.59* |

Note: FMOLS is Pedroni's (2001) fully modified OLS estimator for heterogeneous cointegrated panels. CCE-MG and CCE-P are the mean group and pooled common correlated effects estimators of Pesaran (2006). $t_{PP}$, and $t_{ADF}$ are the Pedroni (1999, 2004) cointegration tests based on the Phillips and Perron $t$ statistics, and the augmented Dickey Fuller $t$ statistic, respectively. $CD$ is Pesaran's (2004) cross-sectional independence test, and $CRMA$ is Sul's (2009) unit root test for the common factors. CADF(p) are CIPS(p) statistics, which are the cross-sectional averages of cross-sectionally augmented Dickey Fuller (CADF(p)) statistics (Pesaran, 2007). The null hypothesis is that all series are non-stationary; the alternative hypothesis is that some series are stationary. Statistical significance at the 5% level or lower is denoted by *.

The middle pane of Table 1 presents tests for the null hypothesis of a unit root in the FMOLS residuals. The $t_{PP}$, and $t_{ADF}$ are the Pedroni (1999, 2004) tests for the null hypothesis of no-cointegration based on the Phillips and Perron $t$-statistics, and the augmented Dickey Fuller $t$-statistic, respectively. Both tests assume cross-sectional independence, and both reject the null of no cointegration. However, Pesaran's (2004) CD test rejects the null hypothesis of cross-sectional independence suggesting that the FMOLS estimates are biased due to the presence of common factors in the residuals (Kao and Chiang, 2000). In fact, the Sul (2009) CRMA statistic, which tests for unit roots in the common factors, fails to reject the null of a unit root in the FMOLS residuals implying that the FMOLS estimates are spurious. Figure 2 illustrates the co-movement of the FMOLS residuals. Note that ignoring cross-sectional dependence would lead to the acceptance of invalid FMOLS results.

In addition to the biased and spurious FMOLS estimates, Table 1 also contains the CCE estimates and residual diagnostic tests. Kapetanios et al. (2010) showed that the CCE estimator of the mean of the slope coefficients is consistent for any number of factors, regardless of whether the common factors are stationary or non-stationary. However, consistent estimation of the model parameters does require that the regression residuals be stationary. The appropriate unit root test should take into account cross-sectional dependence because, if not controlled for, it distorts inference (Banerjee et al., 2004, 2005; Gengenbach et al., 2010). The rejection of unit roots in the CCE regression residuals, $\hat{\epsilon}_{i,t}$ from equation (5), presented in the bottom panel of Table 1, implies that the observed variables and the unobserved factors are cointegrated (Kapetanios et al., 2010).[4]

The CCE estimates presented in the top panel of Table 1 are similar to the elasticities obtained by Nelson et al. (2011), who included in their model observed and deterministic common factors, such as oil prices and a non-linear time trend. The estimated income elasticity of demand for a trip from the U.S. mainland to Hawaii is slightly greater than unity, implying that travel to Hawaii is regarded as a luxury good. Still, our result is close to the 0.996 income elasticity of Nelson et al. (2011), but much lower than the 3.5 of Bonham et al. (2009) who estimated a VECM with cointegrating relationships identified as supply

[4]As long as the residuals are stationary, the CCE pooled (CCE-P) and CCE mean-group (CCE-MG) estimators are both consistent under the random coefficient model assumption (Pesaran and Smith, 1995).

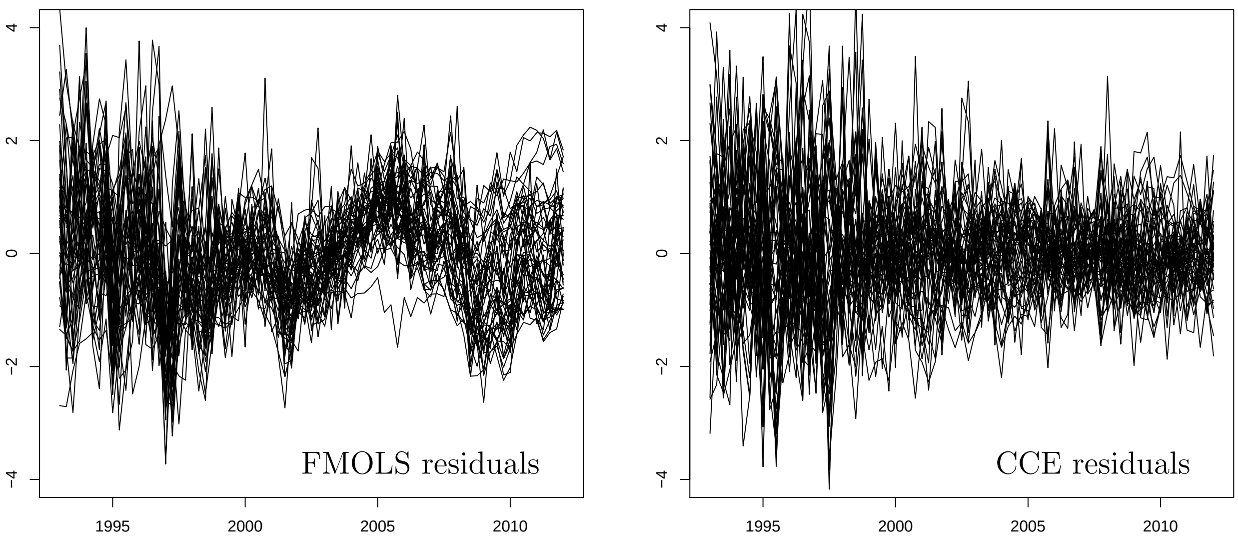


Figure 2: Time plots of standardized FMOLS and CCE residuals.

and demand relations.[5]

Our results indicate that demand for Hawaii travel is inelastic with respect to airfare. If airfare increases by 10%, arrivals to the state are expected to fall by a little more than 2%. Again, this value is fairly close to -0.211, the airfare elasticity estimate of Nelson et al. (2011). The estimated hotel room price elasticity suggests that tourists are more responsive to changes in room rates than to fluctuations in airfare. Facing a \$1000 airline ticket and a daily price of \$200 for a double occupancy room, a couple on a ten-day trip has to split its budget evenly between airfare and accommodation. Still, a 10% drop in the hotel room rate is expected to generate 12% higher visitor arrivals, over five times more than a corresponding drop in airfare. This could be explained by a two stage decision making process on the part of the travelers: in the first stage they choose a destination from a range of competing locations, and in the second stage they pick their flights. The choice in the first stage may be influenced by offerings of free nights, attraction packages, and the overall desirability

[5] As noted in Section 2, the CCE estimator controls for global trends in the panel, and in general produces different results than conventional estimators of time series data lacking a cross-sectional dimension.

of the destination. Because the choice of flights is relegated to the second stage, travelers largely focus on minimizing their airfare to the chosen destination, but do not necessarily switch to competing destinations. As a result, a shift in median airfare from a particular origin to Hawaii only has a modest impact on arrivals.

The Hawaii hotel room rate is independent of trip origin, and it can be considered an observed common factor. Because the CCE estimation procedure is based on an orthogonal projection onto proxies for common factors, the exclusion of the real room rate only has a minor effect on the results: the CCE income elasticity and airfare elasticity estimates are similar for the model with and without lodging prices.[6]

# 4 Conclusion

Estimates of demand elasticities are central to marketing, forecasting and policy work, and where possible, it is natural to turn to the richness of panel data to estimate elasticites. Yet panel estimation using non-stationary data requires careful attention to the likely presence of common shocks in the underlying macroeconomic variables. Our contribution to the literature lies in estimating tourism demand elasticities while accounting for unobserved non-stationary common factors in the data. We deal with cross-sectional dependence of regional variables by applying the CCE estimators proposed by Pesaran (2006) and Kapetanios et al. (2010) to US state level quarterly data spanning the period from the first quarter of 1993 to the first quarter of 2012. We obtain income elasticity slightly over unity, fairly high hotel room price elasticity, but relatively low airfare elasticity. Our results are more realistic than those of Bonham et al. (2009) who's VECM relies only on time-series variation, and are in line with Nelson et al. (2011), who included in their model observed and deterministic common factors, such as oil prices and a non-linear time trend. The advantage of the approach presented in this paper is that it does not require the selection of observable proxies to capture the sources of common shocks, allows the common factors to contain unit roots,

[6]Results with the room rate excluded are available in a working paper version or on request.

and to be correlated with the regressors. In addition, the method offers good finite sample properties, and is relatively simple to implement.

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