Modeling the supply and demand for tourism: a fully identified VECM approach

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Abstract System-based cointegration methods have become popular tools for economic analysis and forecasting. However, identification of structural relationships is often problematic. We estimate a vector error correction model of the supply and demand for Hawaii tourism using a theory-directed sequential reduction method suggested by Hall et al. (2002). We identify reasonable long-run equilibrium relationships, and Diebold and Mariano (1995) tests for forecast accuracy demonstrate satisfactory forecasting performance.

Keywords: Cointegration, Vector error correction model, Identification, Tourism demand and supply analysis, Hawaii.

JEL: C320, L830

1 Introduction

System-based cointegration methods, and their dynamic counterpart vector error correction models (VECMs), have become popular tools for economic analysis and forecasting. Cointegration analysis addresses the problem of spurious regressions among non-stationary time series. Estimation in a system context may shed light on important interrelationships among series while reducing the risk of endogeneity bias.[1]

However, system methods introduce additional challenges; chief among them is the problem of identifying individual structural relationships. In a system with cointegrating rank r, Pesaran and Shin (2001) show that exact identification requires r restrictions in each of the r cointegrating vectors. The popular Johansen (1988, 1991, 1995) method uses a statistical approach to achieve the needed restrictions. Pesaran and Smith (1998) and Pesaran and Shin (2001) criticize this approach as a pure mathematical convenience, and instead advocate a theory-based approach. Hall et al. (2002) argue that the different identification methods proposed in the literature are almost impossible to implement in practice due to the limited sample sizes typically available for empirical research. As an alternative, they suggest testing and imposing theory-based weak exogeneity assumptions at the earliest stage of the model reduction process.

In this paper, we apply the Hall et al. (2002) strategy to the problem of estimating a supply and demand model of Hawaii tourism. There exists a large empirical literature on modeling and forecasting tourism flows. The bulk of these studies estimate tourism demand equations to explain either flows from various source markets into a particular tourism destination, or the allocation of outbound travel to alternative destinations. The overwhelming majority of extant studies use traditional econometric methods and ignore possible supply-side influences.[2]

[1]See Banerjee et al. (1993) for a discussion of finite sample endogeneity bias in error correction models.

[2]For reviews, see Lim (1997), Crouch (1994a,b), Witt and Witt (1992, 1995), and Li et al. (2005). A limited number of tourism studies using cointegration methods exist, but most of these studies rely on single-equation estimation with little or no mention of potential endogeneity problems. (See Kim and Song (1998), Vogt and Wittayakorn (1998), and Song et al. (2000).) Other researchers have recently begun to

Our VECM approach, in contrast, explicitly allows for endogeneity and permits identification of demand and supply relationships. Hawaii is a particularly apt case for such analysis, because tourists from two markets—the mainland United States and Japan—represent a dominant 85% of the total market. Clearly in this case, demand parameters can not be estimated reliably without regard to supply constraints and potential price responses. And of course knowledge of supply behavior is of interest in its own right. Our identified model describes reasonable long-run equilibrium relationships governing tourism demand and supply in Hawaii, and forecasts compare favorably with two competing models according to Diebold and Mariano (1995) tests of forecast accuracy.

The organization of the paper is as follows. Section 2 derives the tourism supply and demand equations and identifies the variables to be used in the modeling exercise. Section 3 outlines our estimation methodology. Section 4 presents the empirical results of the Hawaii tourism model. Section 5 evaluates the forecast performance of the model. Section 6 concludes.

2 A Supply and Demand Model of Tourism

There are relatively few theoretical studies of tourism economics and no unifying conceptual framework. Some early perspectives are reflected in Quandt (1970) and Gray (1970). Sinclair and Stabler (1997), and Mak (2004) provide more recent textbook overviews of tourism theory. In addition, a few researchers have begun to develop optimization-based models of some aspects of the tourism industry (Copeland (1989, 1990); Morely (1992); and Taylor (1995)). While theoretical work is relatively sparse, there exists a well-defined empirical literature, primarily focused on estimating the demand for tourism services. This literature informs the specification of our Hawaii Tourism Model (HTM).

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adopt the system approach (e.g., Kulendran (1996), Lathiras and Siriopoulos (1998), Gangnes and Bonham (1998), and Song and Witt (2000), but identification is obtained exclusively using Johansen's reduced rank regression technique, despite the fact that alternative theory-based identification methods may be superior. Little or no consideration of supply side influences is typically given.

2.1 Tourism Demand

Empirical models of tourism demand borrow heavily from consumer theory (Varian, 1992) which predicts that the optimal consumption level depends on the consumer's income, the price of the good in question, the prices of related goods (substitutes and complements), and other demand shifters. Formally, the Marshallian demand for tourism product can be expressed as,

$$(1) \quad D_{ij} = F(Y_i, P_i, P_j, P_j^S, \mathbf{Z}),$$

where D_{ij} is the tourism product demanded in destination j by consumers from origin country i; Y_i is the income of origin country i; P_i is the price of other goods and services in the origin country i; P_j is the price of tourism product in destination country j; P_j^S is the price of tourism product in competing destinations; and $\mathbf{Z}$ is the vector of other factors affecting tourism demand. Assuming homogeneity, demand can be written as a function of real income and relative destination and substitute prices,

$$(2) \quad D_{ij} = F(\frac{Y_i}{P_i}, \frac{P_j}{P_i}, \frac{P_j^S}{P_i}, \mathbf{Z}).$$

In the literature, there are at least two classes of tourism models, those explaining the distribution of outward flows from a single source market (outbound modeling) and those explaining aggregate tourism flows into a single destination (inbound modeling). For outbound modeling, market shares of visitors or expenditures are the typical dependent variables. For inbound modeling, the most appropriate measure is real expenditures on tourism-related goods and services. However, the unavailability and often poor quality of expenditure data confine the typical study to total visitor arrivals (Anastasopoulos, 1984; O'Hagan and Harrison, 1984). Of the 85 tourism studies reviewed in Crouch (1994b), 63% choose the number of visitor arrivals as the measure of demand while 48% use expenditure and receipts.

Proxies for the demand determinants vary considerably. Typical income measures include gross domestic product, gross national product, national disposable income, personal income and consumption expenditure, measured in either real, nominal, aggregate, or *per capita* form, depending on data availability and the nature of tourism demand being modeled.[3]

Several types of prices appear in the demand specification. The first is the *own price* of tourism products, usually approximated by the consumer price index in the destination market.[4] Second are measures of *substitute prices*. Because domestic travel may substitute for foreign travel, aggregate prices in the country of origin are often included. At the same time, competition among different overseas destinations may call for the inclusion of variables that represent the cost of substitute destinations. Exchange rate adjusted relative prices (*real exchange rates*) are commonly used as proxies for both effects.[5] Finally, transportation costs are sometimes included as a separate factor in determining travel.[6] Many studies augment income and price variables with deterministic effects, including time trends to capture evolving consumer tastes; a constant term to account for "utility image" that does not vary greatly with time; and dummies to account for various once-off events such as

[3]Generally speaking, personal income or consumption expenditures are used to model leisure and holiday travel, while gross domestic or national product and national disposable income are used to model business travel. As for the choice between nominal and real incomes, equations (1) and (2) make it clear that both are acceptable, provided that prices are specified accordingly. A per capita income specification is justified by Witt and Witt (1995) as a solution to the multicollinearity problem when both income and population are used to measure market size.

[4]This practice is sometimes criticized on the grounds that, "the cost of living for local residents does not always reflect the cost of living for foreign visitors to that destination, especially in poor countries" (Song and Witt, 2000). Occasionally tourism-specific prices are employed. For example, Gangnes and Bonham (1998) use the hotel room price. Others (Martin and Witt (1987), Witt and Witt (1992) and Edwards (1995)) argue against the use of tourism-specific indices because their coverage may be suspect and there is little evidence of superior performance.

[5]Martin and Witt (1987) report that the CPI-based *real exchange rate* is a good proxy for tourism cost, while the nominal exchange rate itself is not. Some studies (Kim and Song (1998) and Song et al. (2000)) include *real exchange rates* from a number of competing countries, while others (Vogt and Wittayakorn, 1998) use a single *weighted real exchange rate*. Some authors (Lathiras and Siriopoulos (1998) and Vogt and Wittayakorn (1998)) argue that nominal exchange rates should be included separately from source and destination price levels because tourists may respond very differently to them.

[6]Song and Witt (2000) suggest using, "representative air fares between origin and destination for air travel," as in Fujii et al. (1985) and Crouch (1991). Gangnes and Bonham (1998) reject such practice on the ground that, "frequent discounting and package trips" imply a significantly lower actual price than published fares. Edwards (1995) uses International Air Transport Association (IATA) data on revenues per passenger ton/km. Perhaps because of the data limitation, Li et al. (2005) report that only about 30% or recent tourism demand models included a measure of travel cost.

the Olympic Games, large-scale fairs, foreign currency/travel restrictions and oil crises; seasonality; or changes in data collection methods. These types of events, if otherwise neglected, might lead to bias in the estimated parameters (Anastasopoulos, 1984; Crouch et al., 1992; Kliman, 1981; Mak et al., 1977).

For our Hawaii tourism model (HTM), we use the number of visitor arrivals as the dependent variable because high frequency expenditure data is not available for a sufficiently long continuous time span. We seek to identify demand relationship for each of the two primary Hawaii tourism markets, U.S. mainland and Japanese visitors. Tourists from these two markets consistently account for over 85% of all visitors. To keep the model size manageable, we are forced to choose only the principle determinants of tourism demand while leaving out influences that are deemed less central to our analysis. In addition, some conceptually relevant factors are excluded because of difficulty finding appropriate proxies. The model includes five demand determinants: U.S. real personal income (yr_us), U.S. consumer price index (cpi_us), Japanese real personal income (yr_jp), Japanese *exchange rate adjusted* CPI (cpi_E_jp) and Hawaii average daily hotel room price (prm). The variables used throughout the text are described in Table 1. All series are seasonally adjusted at quarterly frequency and expressed as natural logarithms with the exception of the occupancy rate expressed as a percentage.

2.2 Tourism Supply

Both theoretical and empirical research on the supply of tourism services is scant (Crouch, 1994b). In much of the empirical tourism literature, supply is assumed to be perfectly elastic, and parameters of demand relationships are estimated by Ordinary Least Squares (OLS). However, the infinite elasticity assumption is a convenient simplification rather than a tested hypothesis. Fujii et al. (1985) estimate the supply elasticity of Hawaii lodging services to be close to two, and it is not uncommon to observe sizable fluctuations in hotel room prices. The treatment of supply relationships is therefore indispensable in deriving unbiased demand

Table 1: Summary of Variables in the Hawaii Tourism Model

Mnemonic	Description	Units	Source
Hawaii Variables			
vus	U.S. visitors to Hawaii	thou	DBEDT
vjp	Japanese visitors to Hawaii	thou	DBEDT
prm	Hawaii average daily hotel room rate	dollars	DBEDT
ocup	Hawaii average daily hotel occupancy rate	%	DBEDT
U.S. Variables			
yr_us	U.S. real personal income	bil 82–84$	BEA
cpi_us	U.S. CPI (1982-1984=100)	index	BLS
Japan Variables			
yr_jp	Japan real personal income	bil 95Yen	ESRI
cpi_jp	Japan CPI (1995=100)	index	SBSC
xr_jp	yen/dollar exchange rate	yen/dollar	FED
Calculated Variable			
cpi_E_jp	*cpi_jp/xr_jp*	index	Authors' calc.

Note: Except for the hotel occupancy rate, natural logarithms of each series are used in analysis.
Sources: DBEDT: Department of Business Economic Development and Tourism, State of Hawaii.
BEA: Bureau of Economic Analysis, U.S.
BLS: Bureau of Labor Statistics, U.S.
FED: Federal Reserve Bank at St. Louis.
ESRI: Economic and Social Research Institute, Japan.
SBSC: Statistics Bureau and Statistics Center, Japan.

elasticities, and supply behavior is of interest in its own right.

It is rather difficult to give a precise definition of tourism supply considering the variety of products tourists consume. In this paper, we focus on the supply of accommodations, in part because lodging services represent the single largest component of visitor expenditures in Hawaii and because it is possible to obtain reliable data on hotel room prices.[7] Visitor accommodations are non-storable in nature. A hotel room not rented on a given day is lost forever as a potential source of revenue. As Fujii et al. (1985) have argued, this, together with heavy operating costs, results in a strong incentive for profit maximizing suppliers to maintain high occupancy rates. In the short run, this leads hoteliers to price discriminate and offer off-peak discounts to fill rooms. Over longer horizons, capacity is adjusted through expansion and contraction of room inventory.

One approach to modeling room supply is to estimate an inverted tourism supply curve. Examples appear in the hotel room tax literature (Fujii et al., 1985; Bonham and Gangnes, 1996). The supply price of hotel rooms is assumed to be a mark-up over marginal cost,

$$(3) \quad P_R = markup \cdot MC = M \cdot R(Q_R, P_L, P_K, P_Z),$$

where Q_R is the total quantity of rented rooms; P_L, P_K and P_Z are the input prices of labor, capital and other inputs; and M is the markup factor.

As high frequency data on the number of hotel rooms rented is not available, we use the number of visitors (the sum of U.S. and Japanese tourists) to the islands as a proxy. Assuming that the average length of stay and number of visitors per hotel room are relatively stationary, the total number of rented rooms will share the same trend behavior as the number of visitors. An increase in the number of visitors is then associated with a higher hotel room price. The hotel occupancy rate is used to capture changes in room availability. For a given quantity of rooms rented, an increase in the hotel occupancy rate implies a

[7] Visitors to Hawaii have spent an average of 33% of total expenditures on hotel lodging services over the past three decades.

reduction in the stock of available rooms and therefore an increase in the hotel room price. It would be desirable to include Hawaii-specific input cost measures, but other than local wage rates, such measures do not exist. Considering the limited time span of available data (86 observations) and the number of variables already present in the demand model, we have elected to treat the U.S. consumer price index (*cpi_us*) as a rough proxy for cost influences.

3 Empirical Methodology

We model the supply and demand for tourism services using a vector error correction framework. In this section we present the econometric framework and describe the procedures used to identify the system and select a parsimonious model.

Consider a kth order vector autoregressive (VAR) model for an $m \times 1$ vector of I(1) variables, z_t,

$$(4) \qquad z_t = \Phi_1 z_{t-1} + \cdots + \Phi_k z_{t-k} + c + \epsilon_t \ , \qquad\qquad t = 1, 2, \ldots, T,$$

where Φ_i, $i = 1, 2, \ldots, k$, are $m \times m$ matrices of unknown parameters, c is an $m \times 1$ vector of unknown deterministic terms, ϵ_t is i.i.d. $N(0, \Omega)$, and the initial values, $z_{1-k}, z_{2-k}, \ldots, z_0$ are fixed.[8] The unrestricted VAR in (4) can be reparameterized as a Vector Error Correction Model (VECM),

$$(5) \qquad \Delta z_t = -\Pi z_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta z_{t-i} + c + \epsilon_t \ , \qquad\qquad t = 1, 2, \ldots, T,$$

where $\Pi = I_n - \sum_{i=1}^{k} \Phi_i$, $\Gamma_i = -\sum_{j=i+1}^{k} \Phi_j$, $i = 1, \ldots, k-1$. The equilibrium properties of (5) are characterized by the rank of Π. If all elements of z_t are stationary, Π is a full rank $m \times m$ matrix. If the elements of z_t are I(1) but not cointegrated, Π is rank zero and a

[8] We assume that the roots of $| \ I_n - \Phi_1 \lambda - \Phi_2 \lambda^2 - \cdots - \Phi_k \lambda^k \ | = 0$ lie either on or outside of the unit circle, but rule out the possibility that one or more elements of z_t are I(2). A review of the econometric analysis of I(2) variables is provided in Haldrup (1998).

VAR model in first differences is appropriate. If the elements of z_t are I(1) and cointegrated with $rank(\Pi) = r < m$, Π can be decomposed into two $m \times r$ full column rank matrices α and β where $\Pi = \alpha\beta'$. This implies that there are $r < m$ stationary linear combinations of z_t, such that $\xi_t = \beta' z_t \sim I(0)$. The matrix of adjustment coefficients, α, measures how strongly deviations from the long-run equilibrium, ξ_t, feed back onto the system. Estimation is typically performed using Johansen's reduced rank estimation technique, i.e., the log likelihood is maximized subject to the constraint that Π can be decomposed into two $m \times r$ full column rank matrices α and β such that $\Pi = \alpha\beta'$.

In moving from the unrestricted VAR in (4) to a parsimonious version of the VECM in equation (5) at least four types of restrictions are relevant: restrictions on the rank of the long-run matrix, Π; restrictions on the long-run cointegrating vectors, β; restrictions on the short-run dynamic coefficients, Γ_i's; and restrictions on the loading parameters, α. Researchers have proposed different ways to impose these restrictions (Johansen, 1988, 1991, 1995; Phillips, 1991, 1995; Saikkonen, 993a,b; Pesaran and Shin, 2001). Hall et al. (2002) argue that these approaches are almost impossible to implement in practice when a fairly rich specification encounters a limited sample size. The interaction of dynamic and long-run parameters has enormous effects on the size and power of the statistical tests conventionally adopted. Monte Carlo results in Hall et al. (2002) reveal that imposing valid weak exogeneity restrictions before testing for the cointegrating rank generally improves the power of Johansen rank tests. At the same time, restricting the cointegrating rank has little impact on weak exogeneity tests, at least as long as the rank is not restricted to be less than the true rank.

We follow Hall et al. (2002) and apply the following pragmatic strategy in reducing our general VECM to a more parsimonious representation,

1. Test and impose weak exogeneity restrictions;

2. Test the rank of the long-run matrix, Π (cointegrating rank);

3. Use Johansen's reduced rank procedure to estimate the cointegrating vectors.

4. Test and impose theory based just- and over-identifying restrictions on the cointegrating vector, β.

5. Estimate the complete dynamic model and simplify the dynamics. At this stage, the causality structure of the model is established by eliminating cointegrating vectors with insignificant loading parameters.

Testing Weak Exogeneity

A well known problem with VARs, and particularly important in the identification of a VECM, is the prohibitively large number of parameters. Each equation involves estimating $m \times k$ lag coefficients plus one or more parameters for the deterministic components. Even moderate values of m and k quickly exhaust typical samples for macroeconometric research. For example, with a maximum of four lags, if all eight variables are treated as endogenous, each equation of our HTM requires estimating thirty four parameters, and the system as a whole has 272 coefficients. Setting aside sufficient data for out-of-sample forecast evaluation, leaves us with a sample of only eighty six observations (1980Q1–2001Q2), and the VAR approach quickly runs into the problem of severe lack of degrees of freedom. In-sample regressions fit exceedingly well, but out-of-sample forecasts are generally poor.

One way to address the over-parameterization problem is to test and impose weak exogeneity assumptions. For each series treated as weakly exogenous, the number of equations in the system is reduced by one and the number of parameters by $(mk + d)$, where d is the number of deterministic components. For the HTM, if the external drivers (yr_us, yr_jp, cpi_us, cpi_E_jp) are treated as weakly exogenous, the number of equations is reduced from eight to four and the number of parameters to estimate is reduced from 272 to 136.

To see the effect of weak exogeneity on the system, partition the m-vector of I(1) random variables z_t into the n-vector y_t and the q-vector x_t such that $z_t = (y_t{}', x_t{}')'$ and $q = m - n$. Our primary interest is the structural modeling of y_t conditional on its own past values,

y_{t-1}, y_{t-2}, ..., and the current and past values of x_t. The parameters, matrices, and errors in the VECM equation (5) can be partitioned conformably as $c = (c'_y, c'_x)'$, $\alpha = (\alpha'_y, \alpha'_x)'$, $\Gamma_i = (\Gamma'_{yi}, \Gamma'_{xi})'$, $i = 1, 2, \ldots, k-1$, $\epsilon_t = (\epsilon'_{yt}, \epsilon'_{xt})'$, and the variance-covariance matrix as

$$(6) \quad \Omega = \begin{pmatrix} \Omega_{yy} & \Omega_{yx} \\ \Omega_{xy} & \Omega_{xx} \end{pmatrix}.$$

The model is transformed into a conditional model for y_t and a marginal model for x_t,

$$\begin{aligned} (7) \quad \Delta y_t &= (c_y - \omega c_x) + \omega \Delta x_t + (\alpha_y - \omega \alpha_x)\beta' z_{t-1} + \sum_{i=1}^{k-1} (\Gamma_{yi} - \omega \Gamma_{xi}) \Delta z_{t-i} \\ &\quad + (\epsilon_{yt} - \omega \epsilon_{xt}), \\ (8) \quad \Delta x_t &= c_x + \alpha_x \beta' z_{t-1} + \sum_{i=1}^{k-1} \Gamma_{xi} \Delta z_{t-i} + \epsilon_{xt}, \end{aligned}$$

where $\omega = \Omega_{yx}\Omega_{xx}^{-1}$.

For the system in equation (7) and (8), the parameters of interest, β', enter both the conditional and the marginal model, and the adjustment coefficients $(\alpha_y - \omega\alpha_x)$ depend on the covariance matrix, Ω, and all the adjustment coefficients (α_y, α_x). Therefore, the parameters of interest cannot be variation free, and a full system analysis is required.[9] When the parameters of interest are the cointegrating vector β', x_t is weakly exogenous if and only if $\alpha_x = 0$ (Johansen, 1991). In this case, equation (7, 8) may be written:

$$\begin{aligned} (9) \quad \Delta y_t &= (c_y - \omega c_x) + \omega \Delta x_t + \alpha_y \beta' z_{t-1} + \sum_{i=1}^{k-1} (\Gamma_{yi} - \omega \Gamma_{xi}) \Delta z_{t-i} + (\epsilon_{yt} - \omega \epsilon_{xt}), \\ (10) \quad \Delta x_t &= c_x + \sum_{i=1}^{k-1} \Gamma_{xi} \Delta z_{t-i} + \epsilon_{xt}, \end{aligned}$$

The condition $\alpha_x = 0$ ensures that β does not appear in the marginal distribution for x_t

[9] Two conditions must be satisfied for x_t to be weakly exogenous (Hall et al., 2002). 1) The parameters of interest are functions of the parameters in the conditional model alone. 2) The parameters in the conditional model and the parameters in the marginal model are variation-free; that is, they do not have any joint restrictions.

in equation (10), and that α_x does not appear in the conditional model in equation (9). Therefore, the conditional model (9) contains as much information about the cointegrating relationships, $\beta' z_{t-1}$, as the full system, and analysis of the conditional model alone is sufficient.

Following Hall et al. (2002), once weak exogeneity restrictions are tested and imposed, Johansen rank tests are conducted.[10] The resulting tests benefit from greater power than tests conducted without the theory-based exogeneity restrictions.

Restricting Cointegrating Vectors

Even with a known rank for the long run matrix, Π, an identification problem arises because the matrices α and β are not uniquely identified without additional information. To see this, note that for any $r \times r$ non-singular matrix Q we can define matrices $\alpha^* = \alpha Q$ and $\beta^{*'} = Q^{-1}\beta'$ such that $\Pi = \alpha^* \beta^{*'} = \alpha Q Q^{-1} \beta' = \alpha\beta'$. Pesaran and Shin (2001) show that r^2 restrictions are needed for exact identification. The restrictions must be evenly distributed across the cointegrating vectors, i.e., there must be r restrictions per vector.

The most common approach to imposing the r^2 identifying restrictions is Johansen's statistical approach. Specifically, Johansen's just identified estimator of β is obtained by selecting the r largest eigenvectors of the system, subject to "ortho-normalization" and "orthogonalization" restrictions. Pesaran and Shin (2001) criticize this approach as "pure mathematical convenience" rather than an economically justified approach.[11] They emphasize the use of economic theory to guide the choice of long-run exact/over identifying restrictions. The theory-guided approach takes Johansen's just identified vector β_J as given and replaces the "statistical" restrictions with ones that are economically meaningful.

In the following section we adopt the pragmatic reduction strategy of Hall et al. (2002),

[10] The methodology for testing the rank of Π is well known, addressed in standard graduate level econometrics texts (see, e.g., Davidson and MacKinnon (2004)), and for that reason will not be covered here.

[11] Another non-theoretical method of identification is the triangularization approach of Phillips (1991, 1995).

testing for weak exogeneity, testing for cointegrating rank, and applying theory based exact and over identifying restrictions to the cointegrating vectors.

4 The Hawaii Tourism Model

Historical data for the HTM variables on a quarterly basis is available for the 1980 to 2005 period. To preserve data for out-of-sample forecast evaluation, we identify the model using a truncated sample from 1980Q1 through 2001Q2. This choice maximizes our sample period for initial estimation and identification, avoids the difficult task of modeling the September 11, 2001 (9/11) shock to Hawai‘i tourism, and preserves a sufficiently large post-estimation period for out-of-sample forecast evaluation.

Weak Exogeneity

We begin with the vector of eight variables, z_t=(vus, vjp, prm, $ocup$, yr_us, cpi_us, yr_jp, cpi_E_jp) discussed in section 2. We hypothesize that the four tourism variables, y_t=(vus, vjp, $prm, ocup$), are endogenous, and the remaining external factors, x_t=(yr_us, cpi_us, yr_jp, cpi_E_jp), are exogenous. For a system with eight variables, there can exist at the most seven cointegrating vectors.[12] Following the strategy outlined in section 3, we leave the cointegrating rank unrestricted ($r = 7$) and test the null hypothesis, $H_0 : \alpha_x = 0$ for each candidate exogenous variable. (That is, we exclude all cointegrating vectors from equations explaining the "theoretically" exogenous variables.) We cannot reject the weak exogeneity of U.S real income, yr_us, or the exchange-rate-adjusted Japanese price level, cpi_E_jp; tests for both variables have p-values in excess of 10% (see Table 2, Panel 1). In contrast, weak exogeneity of both the U.S. price level, cpi_us, and Japanese real income, yr_jp is strongly

[12] We treat all variables in the HTM as I(1). In Zhou et al. (2004), we report augmented Dickey Fuller (Dickey and Fuller, 1979, 1981), Schwert (1989) and Perron (1990) tests for unit roots in each variable studied here. We select the lag length for our initial VAR by estimating a VAR in levels with a maximum of five lags and sequentially reducing the lag length by one lag until we maximize the Schwarz information criterion subject to non-rejection of the null hypothesis of no serial correlation up to lag 6. We select a lag length of 4. (Results of these tests are available from the authors on request.)

Table 2: Weak Exogeneity Tests

$$\Delta y_t = (c_y - \omega c_x) + \omega \Delta x_t + (\alpha_y - \omega \alpha_x)\beta' z_{t-1} + \sum_i^{k-1} (\Gamma_{yi} - \omega \Gamma_{xi}) \Delta z_{t-i} + (\epsilon_{yt} - \omega \epsilon_{xt}) \quad (9)$$

$H_0 : \alpha_x = 0$

Panel 1: $rank(\Pi) = 7$

Variable	$\chi^2(7)$	p-value
yr_us	10.42	0.17
cpi_us	37.67	**0.00**
yr_jp	31.90	**0.00**
cpi_E_jp	11.02	0.14

Panel 2: Harbo Weak Exogeneity Tests

Variable	F-test	p-value
yr_us	0.34	0.79
cpi_us	1.21	0.32
yr_jp	2.64	0.06
cpi_E_jp	0.03	0.99

Note: Column 1 lists the variables tested for weak exogeneity. Column 2 presents the χ^2 statistic (F statistic in the case of Panel 3) for the null hypothesis of weak exogeneity. Column 3 presents the marginal significance level of the statistic in Column 2 to two decimal places.

rejected at the 1% level.[13]

While $\alpha_x = 0$ is a necessary and sufficient condition for weak exogeneity of x_t with respect to β, this condition often proves to be too strong in practice because exogenous variables may form cointegrating relationships among themselves (Pesaran et al., 2000). In our case, because of macroeconomic relationships within and between the U.S. and Japan, it is likely that our vector, $x_t = (yr\_us, cpi\_us, yr\_jp, cpi\_E\_jp)$ of hypothesized weakly exogenous variables is cointegrated.[14] The rejection of $\alpha_x = 0$ may occur due to cointegration among the exogenous variables, rather than because of their endogeneity for the parameters of interest in the HTM. Nevertheless, weak exogeneity can still be tested following the approach suggested by Harbo et al. (1998). Instead of estimating the whole system and testing whether a subset of α is zero, they suggest estimating the conditional

[13]Because weak exogeneity depends on model specification, Hall et al. (2002) suggest exogenizing any non-rejecting weakly exogenous variables and re-testing the remaining variables. Treating *yr_us* and *cpi_E_jp* as weakly exogenous, we re-estimate the system with six endogenous variables, two exogenous variable, and five unrestricted cointegrating vectors, $r = 5$. Test results (not shown) continue to strongly reject the null hypothesis of weak exogeneity of both *cpi_us* and *yr_jp* at less than 1% significance level.

[14]Using a restricted trend, unrestricted intercept VAR specification, we can not reject the hypothesis that there is at least one cointegrating relationship among the four variables.

model alone and checking for weak exogeneity by adding the empirically derived cointegrating relationships to the marginal model. The null hypothesis of weak exogeneity implies that in the marginal model the loading parameters on the estimated equilibrium relationships are insignificantly different from zero.

Results from the Harbo test for weak exogeneity are reported in Panel 2 of Table 2, (but note that the cointegrating vectors used in these tests are identified in section 4 below). The first differences of "exogenous" variables (Δyr_us, Δcpi_us, Δyr_jp and Δcpi_E_jp) are each regressed on the lagged first differences of all variables, the three identified cointegrating vectors and a constant. We test the joint null hypothesis that the loading parameter on all three cointegrating vectors are insignificantly different from zero in each equation in the marginal system. F-tests for this null hypothesis are presented in Panel 2 of Table 2. We do not reject the null hypothesis of weak exogeneity for any of the variables in the x_t=(yr_us, cpi_us, yr_jp, cpi_E_jp) vector at the 5% marginal significance level. Below we test for the rank of the cointegrating space subject to these weak exogeneity restrictions.

Cointegrating Rank

Imposing the weak exogeneity restrictions tested above, we proceed to test the rank of the long run matrix, Π, using Johansen's reduced rank methodology. Table 3 reports the test statistics and the corresponding asymptotic critical values at the 5% and 10% significance levels, as tabulated in *Table T.4* of Pesaran et al. (2000) for a system with four weakly exogenous variables. Based on both the trace and maximum eigenvalue statistics, we reject the null of both zero and one or fewer cointegrating vector at the 5% significance level. The null of two or fewer cointegrating vectors is rejected at the 10% level using the trace test but not the maximum eigenvalue test. Because of the potential of three cointegrating relationships, and our objective of modeling two demand and one supply relationships, we proceed under the assumption that the system has three cointegrating vectors.

Table 3: COINTEGRATION RANK TESTS

	Trace Test			Max Eigenvalue Test		
H(r)	Statistic	0.05	0.10	Statistic	0.05	0.10
$r = 0$	**139.30**	99.11	93.98	**52.82**	43.75	41.01
$r \leq 1$	**86.48**	69.84	65.90	**42.80**	37.44	34.66
$r \leq 2$	**43.68**	45.10	41.57	23.78	30.55	27.86
$r \leq 3$	19.90	23.17	20.73	19.90	23.17	20.73

Note: Column 1 lists the null hypothesis of zero, at least one, two, three, four cointegrating vectors; Column 2 lists the *trace statistic*; Column 3 and 4 are the critical values for *trace statistic* at 5% and 10% significance levels from *Table T.4* of Pesaran et al. (2000); Column 5 lists the *maximum eigenvalue statistic*; Column 6 and 7 are the critical values for *maximum eigenvalue statistic* at 5% and 10% significance levels from *Table T.4* of Pesaran et al. (2000); Bolded numbers indicate significance at 10% level.

Long-run Cointegrating Vectors

Our goal here is to identify three long run equilibrium relationships, $\beta' z_{t-1}$, where β' is the 3×9 matrix of unrestricted cointegrating parameters.[15] We apply theory driven restrictions under the assumption that the three cointegrating vectors (β_1, β_2, and β_3) represent the demand for tourism services by U.S. visitors, demand by Japanese visitors, and the supply of Hawaii tourism services. To obtain the just identified system, we impose $r = 3$ restrictions per equation. In the cointegrating vector representing U.S. visitor demand, equation (11), we normalize on U.S. visitor arrivals, vus, and exclude Japanese visitor arrivals ($\beta_{1,2} = 0$) and Japanese real income, ($\beta_{1,7} = 0$). In the vector representing Japanese visitor demand (12) we normalize on Japanese visitor arrivals, and exclude U.S. visitor arrivals ($\beta_{2,1} = 0$) and U.S. real income ($\beta_{2,5} = 0$). Finally, for the supply vector (13) we normalize on the hotel room price, and exclude both U.S. and Japanese income ($\beta_{3,5}, \beta_{3,7} = 0$). The resulting

[15] Following Pesaran et al. (2000), we allow for an unrestricted intercept in the VECM (5) and restrict time trends to lie in the cointegrating space. We can then test the hypothesis that the time trend can be excluded from the cointegrating vectors.

just identified system is given by the following equations:

$$
\begin{aligned}
(11) \quad vus &= \beta_{1,3} \cdot prm + \beta_{1,4} \cdot ocup + \beta_{1,5} \cdot yr\_us + \beta_{1,6} \cdot cpi\_us + \beta_{1,8} \cdot cpi\_E\_jp \\
&\quad + \beta_{1,9} \cdot trend + \xi_{Dus}, \\
(12) \quad vjp &= \beta_{2,3} \cdot prm + \beta_{2,4} \cdot ocup + \beta_{2,6} \cdot cpi\_us + \beta_{2,7} \cdot yr\_jp + \beta_{2,8} \cdot cpi\_E\_jp \\
&\quad + \beta_{2,9} \cdot trend + \xi_{Djp}, \\
(13) \quad prm &= \beta_{3,1} \cdot vus + \beta_{3,2} \cdot vjp + \beta_{3,4} \cdot ocup + \beta_{3,6} \cdot cpi\_us + \beta_{3,8} \cdot cpi\_E\_jp \\
&\quad + \beta_{3,9} \cdot trend + \xi_S.
\end{aligned}
$$

Parameter estimates are reported in Table 4. This system of equations serves as the starting point for tests of over-identifying restrictions presented below.

Table 4: Just Identified System

U.S. Visitor Demand					
$vus = \beta_{1,3} \cdot prm + \beta_{1,4} \cdot ocup + \beta_{1,5} \cdot yr\_us + \beta_{1,6} \cdot cpi\_us + \beta_{1,8} \cdot cpi\_E\_jp + \beta_{1,9} \cdot t + \xi_{Dus}$ (11)					
$\beta_{1,3}$	$\beta_{1,4}$	$\beta_{1,5}$	$\beta_{1,6}$	$\beta_{1,8}$	$\beta_{1,9}$
-9.58	-4.19	25.89	16.44	0.46	-0.19
(2.70)	(4.52)	(7.26)	(8.66)	(0.73)	(0.09)

Japanese Visitor Demand					
$vjp = \beta_{2,3} \cdot prm + \beta_{2,4} \cdot ocup + \beta_{2,6} \cdot cpi\_us + \beta_{2,7} \cdot yr\_jp + \beta_{2,8} \cdot cpi\_E\_jp + \beta_{2,9} \cdot t + \xi_{Djp}$ (12)					
$\beta_{2,3}$	$\beta_{2,4}$	$\beta_{2,6}$	$\beta_{2,7}$	$\beta_{2,8}$	$\beta_{2,9}$
-1.83	1.70	-3.04	4.82	0.02	0.03
(0.44)	(0.60)	(1.15)	(0.89)	(0.12)	(0.01)

Supply					
$prm = \beta_{3,1} \cdot vus + \beta_{3,2} \cdot vjp + \beta_{3,4} \cdot ocup + \beta_{3,6} \cdot cpi\_us + \beta_{3,8} \cdot cpi\_E\_jp + \beta_{3,9} \cdot t + \xi_S$ (13)					
$\beta_{3,1}$	$\beta_{3,2}$	$\beta_{3,4}$	$\beta_{3,6}$	$\beta_{3,8}$	$\beta_{3,9}$
0.44	0.43	1.89	-0.24	-0.26	0.01
(0.11)	(0.11)	(0.46)	(0.59)	(0.09)	(0.00)
log likelihood = 1288.23					

Note: Each column presents parameter estimates and standard errors in parentheses. Computations are carried out using *PcGive 10*.

U.S. Tourism Demand

To identify a U.S. tourism demand relationship, we test 4 over-identifying restrictions. We test exclusion restrictions on the occupancy rate, *ocup*, and Japanese consumer prices, *cpi_E_jp*; a homogeneity restriction on the hotel room price, *prm*, and the U.S. consumer price index, *cpi_us*, ($\beta_{1,1} = -\beta_{1,4}$); and a restriction on the magnitude of the U.S. income elasticity. Note that the income elasticity in the just-identified U.S. demand relationship is implausibly large and estimated quite imprecisely. While the tourism literature often reports income elasticities in excess of two, we restrict the elasticity to the smallest statistically acceptable value, because we expect that a larger income elasticity will adversely impact the forecasting performance of the HTM. We cannot reject the restriction that the U.S. real income elasticity ($\beta_{1,3}$) is 3.5, but smaller values are rejected. The estimated relative price elasticity of -0.55 is well within the range of estimates reported in the literature.[16] The resulting U.S. demand relationship is presented in Table 5

Japanese Tourism demand

To identify a Japanese tourism demand equation, we test four over-identifying restrictions similar to those used for U.S. tourism demand. We test exclusion restrictions on the hotel occupancy rate, *ocup*, U.S. consumer prices, *cpi_us*, and the time trend. In addition, we test one homogeneity restriction on the hotel room price and Japanese prices, *prm* and *cpi_E_jp*, ($\beta_{2,1} = -\beta_{2,5}$). The Japanese income elasticity is left unrestricted as there is no indication in the literature of a good estimate and the estimated elasticity is an economically reasonable

[16] Witt and Witt (1995) find that income elasticities tend to exceed unity, consistent with the notion that international travel is a luxury good. For a sample of fourteen models from four studies, they report a median income elasticity of 2.4. Edwards (1995) obtains an income elasticity of 5 for U.S. travelers to Asia-Pacific region. Sheldon (1993) surveys ten econometric studies of tourism expenditures from 1966 to 1987 for a wide range of source-destination pairs including U.S. travel to Canada, Europe, and Mexico, Canadian tourism to the U.S. and other countries and U.S. destination tourism by major foreign countries. He finds a large range for income elasticities (from -0.15 to 6.6) with a median of 2.2.

Comparison of price elasticity estimates is more difficult because of the many alternative price measures used. Witt and Witt (1995) report a median own price elasticity of -0.7 for studies using destination cost. Sheldon (1993)'s results imply a median destination price elasticity of -1.2, and an exchange rate elasticity of -1.6. Again, the range of price elasticity estimates is very large, for destination prices ranging from -7.3 to 1.6 and for exchange rates from -7.6 to 4.1.

Table 5: Over Identified System

U.S. Visitor Demand

$$vus = \beta_{1,3} \cdot prm + \beta_{1,4} \cdot ocup + \beta_{1,5} \cdot yr\_us + \beta_{1,6} \cdot cpi\_us + \beta_{1,8} \cdot cpi\_E\_jp + \beta_{1,9} \cdot t + \xi_{Dus} \quad (11)$$

$\beta_{1,3}$	$\beta_{1,4}$	$\beta_{1,5}$	$\beta_{1,6}$	$\beta_{1,8}$	$\beta_{1,9}$
-0.55	0	3.5	0.55	0	-0.02
(-0.31)	-	(0.0)	(0.31)	-	(0.00)

Japanese Visitor Demand

$$vjp = \beta_{2,3} \cdot prm + \beta_{2,4} \cdot ocup + \beta_{2,6} \cdot cpi\_us + \beta_{2,7} \cdot yr\_jp + \beta_{2,8} \cdot cpi\_E\_jp + \beta_{2,9} \cdot t + \xi_{Djp} \quad (12)$$

$\beta_{2,3}$	$\beta_{2,4}$	$\beta_{2,6}$	$\beta_{2,7}$	$\beta_{2,8}$	$\beta_{2,9}$
-0.37	0	0	2.23	0.37	0
(-0.09)	-	-	(0.13)	(0.09)	-

Supply

$$prm = \beta_{3,1} \cdot vus + \beta_{3,2} \cdot vjp + \beta_{3,4} \cdot ocup + \beta_{3,6} \cdot cpi\_us + \beta 3,8 \cdot cpi\_E\_jp + \beta_{3,9} \cdot t + \xi_S \quad (13)$$

$\beta_{3,1}$	$\beta_{3,2}$	$\beta_{3,4}$	$\beta_{3,6}$	$\beta_{3,8}$	$\beta_{3,9}$
0.54	0.13	1.83	0	0	0.01
(0.10)	(0.07)	(0.42)	-	-	(0.00)

log likelihood = 1279.23

LR-test, $\chi^2(10) = 18.01$ [0.055]

Note: Each column presents parmaeter estimates and standard errors in parentheses. The last panel of the table presents the Likelihood Ratio test for the joint null that all over-identifying restrictions are valid. The marginal significance level for this test is in brackets. Computations are carried out using *Pc-Fiml 9.10*.

2.23. The relative price elasticity estimate of -0.37 falls well within the range of other studies. The resulting Japanese demand relationship is presented in Table 5.

Hawaii Tourism Supply

To identify a Hawaii tourism supply relationship we test two over-identifying restrictions; we exclude both the U.S. and Japanese price levels (*cpi_us* and *cpi_E_jp*). While we have eliminated any possible proxy for production costs, both the occupancy rate and the number of visitors have the correct sign, and it is possible that the deterministic trend and/or occupancy rate also proxy for production costs. We tested and rejected the restriction that U.S. and Japanese visitors enter the supply equation with the same coefficient. The implied weighted-average supply price elasticity is 2.4, similar to the estimate of approximately 2 found by Fujii et al. (1985). The resulting Supply relationship is presented in Table 5.

Taken as a group, we cannot reject these overidentifying restrictions at the 5% level. The likelihood ratio statistic for the joint test of all overidentifying restrictions has a value of 18, and a marginal significance level of 5.5%. (The relatively low significance level results primarily from the large magnitude of the restriction on the U.S. income elasticity.) The overidentified cointegrating relationships presented in Table 5 represent the long-run equilibria of the system. Below we further restrict the system by testing and imposing zero restrictions on system dynamics.

4.1 The Dynamic Model

The dynamic VECM is written,

$$(14)\quad \Delta y_t = c + \omega \Delta x_t + \sum_{i=1}^{3} \Gamma_i \Delta z_{t-i} + \alpha_1 \xi_{Dus} + \alpha_2 \xi_{Djp} + \alpha_3 \xi_S + u_t$$

where ξ_{Dus}, ξ_{Djp}, and ξ_S are the three equilibrium errors from equations (11)–(13), and α_1, α_2, and α_3 are 3×1 vectors of loading parameters. Pulse-type dummy variables are included for the 1985 United Airlines strike and the 1991 Person Gulf War. At this stage, dynamics are simplified by dropping statistically insignificant terms. This involves excluding first differenced terms with t-values less than 2, starting from the smallest. The error correction terms are eliminated by the same criterion. A total of 58 zero restrictions are applied. The joint test of all zero restrictions produces a χ^2 statistic of 30.75 with a p-value of 0.99. We do not reject these exclusion restrictions at 1% level. The estimated loading parameters and corresponding diagnostic test statistics are shown in Table 6.

The estimated system appears to be an adequate model for Hawaii tourism activity. All equations perform reasonably well, explaining 51%, 62%, 46%, and 65% of the variation in Δvus, Δvjp, Δprm, and $\Delta ocup$, respectively. All equations pass all diagnostic tests at the 5% significance level. The existence of long-run equilibrium error terms in model equations allows for temporary disequilibrium between causal variables and the demand and

Table 6: Dynamic Model: Loading Parameters and Diagnostics

Equation	α_1	α_2	α_3	$\bar{R}^2$	AR1-5	Normality	Arch
Δvus	-0.11		0.33	0.51	2.25	2.05	0.32
	(-5.18)		(5.04)		[0.07]	[0.36]	[0.86]
Δvjp		-0.34	-.13	0.62	2.32	1.68	0.19
		(-4.57)	(-1.57)		[0.06]	[0.43]	[0.94]
Δprm	-0.09		-0.16	0.46	2.15	0.83	1.06
	(-5.06)		(-4.43)		[0.08]	[0.66]	[0.38]
$\Delta ocup$	-0.02	-0.10	0.22	0.65	2.21	1.25	0.35
	(-1.25)	(-3.59)	(5.86)		[0.07]	[0.53]	[0.84]

log likelihood = 1263.85
LR-test, $\chi^2(58) = 30.75$ [0.99]

Note: Column 1 lists the dependent variable of individual equations in the system; Column 2 to 4 give the loading parameters, $\alpha_1 - \alpha_3$ and the corresponding *Student* t-statistic for the three identified cointegrating vectors; Column 5 presents the coefficient of determination R^2; Column 6 gives an F-test (and corresponding p-value) for the null hypothesis that the equation residuals are independent up to lag 5. Column 7 is a χ^2 test (and p-value) for the null hypothesis that the regression residuals are normally distributed. Column 8 is a test for the null that the residuals do not exhibit autoregressive conditional heteroscedasticity (ARCH) (Engle, 1982). Figures in parenthesis (.) are the *Student* t-statistics corresponding to the loading parameters whereas those in brackets [.] are p-values for individual tests.Computations are carried out using *Pc-Fiml 9.10* with the exception of the R^2 which are calculated using RATS v 5.0.

supply variables. The adjustment factor (α's) captures the speed of adjustment toward the equilibrium relationship. For example, if U.S. arrivals are less than predicted by U.S. real income growth and the relative cost of a Hawaii vacation, arrivals would increase over time to eliminate the disequilibrium error. The three long-run equilibrium errors enter the four equations differently. The equation for U.S. visitor growth, Δvus, contains both ξ_{Dus} and ξ_S. The loading parameter on the U.S. demand equilibrium error, ξ_{Dus}, is -0.11, so 11% of the equilibrium error is corrected each period. In the equation for Japanese visitor growth, Δvjp, the equilibrium error associated with Japanese visitor demand, ξ_{Djp}, enters with a coefficient of -.34, implying complete adjustment towards equilibrium in slightly less than three quarters. The equilibrium errors for U.S. demand, ξ_{Dus}, and the supply relationship, ξ_S, enter the hotel room price equation, Δprm, while all thee errors enter the equation for the change in hotel occupancy, $\Delta ocup$. In the case of the Japanese visitor demand equation, the equilibrium error for the supply relationship, ξ_S, is retained despite the fact that its t-value (-1.57) is below the 5% critical value. The same is true for the U.S. demand equilibrium error in the occupancy rate equation. In both cases excluding these equilibrium errors led to a rejection of the null hypothesis of no serial correlation (up to lag five) in the equation residuals. To more fully evaluate the performance of the HTM, we perform out of sample forecast evaluation below.

5 Forecast Evaluation

This section evaluates the forecasting performance of the newly identified HTM. To preserve data for out-of-sample forecast evaluation, we identified the HTM and its rivals using a truncated sample from 1980Q1 through 2001Q2. This also allowed us to avoid the difficulty of modeling the significant shock to Hawaii tourism from the September 11, 2001 terrorism attacks. In the years since 9/11, Hawaii tourism has also been adversely affected by terrorism worries, anthrax scares, the invasion of Afghanistan followed by the War in Iraq, and the outbreak of Severe Acute Respiratory Syndrome and Avian flu. As a result, the period since 9/11 represents a particularly challenging one for forecasting.[17]

We compare forecasts from the HTM with those from two rival models. Both rival models are VARX systems (vector autoregressions with exogenous variables), one in log levels (LVARX) and the other in log first differences (DLVARX). The LVARX in levels admits the possibility of cointegration but does not impose cointegrating restrictions as in the HTM, while the DLVARX in differences has the advantage of converting some forms of structural change into one period shocks. In both cases, the rival models are identified (one equation at a time) using the model selection algorithm in PcGETS 10.3 (Hendry and Krolzig, 2001).[18] Specifically, we construct a Generalized Unrestricted Model (GUM) in log levels (or differences) for each endogenous variable in the HTM just identified system. That

[17]See Bonham et al. (2006) for an analysis of the impact of 9/11 and other shocks to U.S. and Hawai‘i tourism.

[18]See Krolzig (2003) for an evaluation of the use of the PcGETS algorithms to identify structural VARs.

is, each endogenous variable is explained by up to four lags (three in the differenced model) of each of the four endogenous and four weakly exogenous variables, and we make use of the theory motivated exclusion restrictions used in the just-identified model presented in Table 4.[19] PcGETS is used in its default "liberal-testimation" mode. In the liberal mode significance levels are adjusted to minimize the non-selection probability, i.e., keep as many of the GUM variables as possible, at the risk of retaining irrelevant variables more often. Trivedi (1984) characterized such an algorithm as "testimation." While we do not explicitly include a naive no change or random walk alternative, as is often done in this literature, it is important to note that the PcGETS algorithm may select a random walk specification from either the LVARX or DLVARX GUM. Estimation results are not reported here but are available upon request.

As described above, we initially identified each model specification over the sample period 1980Q1-2001Q2. Each model is then used to generate dynamic forecasts from four to twelve steps ahead. The sample is then rolled forward one quarter, and another set of four- through twelve-step ahead dynamic forecasts are generated.[20] We obtain 12 four-step, 8 eight-step and 4 twelve-step ahead dynamic forecasts.

Rather than simply rank the rival models based on a variety of loss functions such as mean absolute percent error (MAPE) or mean squared error (MSE), we test the accuracy of the out of sample forecasts from the HTM relative to the accuracy of the LVARX and DLVARX competitors using the Diebold and Mariano (1995) test.

For two forecasts (with errors e_{1t} and e_{2t}), the null hypothesis of equal forecast accuracy is $E[L(e_{1t}) - L(e_{2t})] = 0$, where $L(\cdot)$ is the loss associated with a particular forecast error.

[19] As for the HTM, we also include dummy variables for the 1985 United Airlines strike and the 1991 Persian Gulf War.

[20] All models are re-estimated, but not re-selected, once every four quarters.

The Diebold and Mariano (1995) test statistic is

$$(15) \qquad S_1 = \frac{\bar{d}}{\sqrt{\hat{V}(\bar{d})}},$$

where

$$\bar{d} = \frac{1}{n}\sum_{t=1}^{n} d_t,$$

$$d_t = L(e_{1t}) - L(e_{2t}),\ t = 1, \ldots, n$$

and $$\hat{V}(\bar{d}) = \frac{1}{n}[\hat{\gamma}_0 + 2\sum_{k=1}^{h-1}\hat{\gamma}_k],$$

and the autocovariance $\hat{\gamma}_k$ is estimated as,

$$(16) \quad \hat{\gamma}_k = \frac{1}{n}\sum_{t=k+1}^{n}(d_t - \bar{d})(d_{t-k} - \bar{d})$$

Under the null hypothesis, the statistic S_1 has an asymptotic normal distribution. To reduce the tendency for the test to be oversized as the forecast horizon increases, we use Harvey et al.'s (1998) modification,

$$(17) \quad S_1^* = [\frac{n + 1 - 2h + n^{-1}h(h-1)}{n}]^{1/2} \cdot S_1.$$

We compare S_1^* to the appropriate critical value using the t-distribution with (n-1) degrees of freedom. We assume an MSE loss function, so that:

$$(18) \quad d_t = L(e_{1t}) - L(e_{2t}) = (e_{1t})^2 - (e_{2t})^2.$$

We construct pairwise rankings for each of the three competing models for each endogenous variable: U.S. visitor demand, Japanese visitor demand, the hotel room price, and the occupancy rate. Tables 7 - 9 present results for the four-, eight-, and twelve-step-ahead forecasts respectively. In the relatively short-term four-step-ahead forecasts, no model totally dominates in the MSE rankings. The DLVARX produces the lowest MSE for two of the four variables; both the HTM and the LVARX models produce the lowest MSE for one of the four variables. Based on the Diebold and Mariano test, the HTM produces forecasts

Table 7: 4-Step-Ahead Forecast Comparisons 2001:3-2005:1

U.S. Visitor Demand	MSE	$H_0: MSE_i = MSE_j$ vs $H_a: MSE_i < MSE_j$		
Model j/Model i		HTM	LVARX	DLVARX
HTM	0.0102		0.999	0.212
LVARX	0.0194	<u>0.001</u>		
DLVARX	**0.0058**	0.788		
Japanese Visitor Demand	MSE	$H_0: MSE_i = MSE_j$ vs $H_a: MSE_i < MSE_j$		
Model j/Model i		HTM	LVARX	DLVARX
HTM	**0.0325**		0.951	0.970
LVARX	0.0455	<u>0.049</u>		
DLVARX	0.0778	<u>0.030</u>		
Room Price– Supply	MSE	$H_0: MSE_i = MSE_j$ vs $H_a: MSE_i < MSE_j$		
Model j/Model i		HTM	LVARX	DLVARX
HTM	0.0008		0.999	<u>0.001</u>
LVARX	0.0021	<u>0.000</u>		
DLVARX	**0.0007**	0.999		
Occupancy Rate	MSE	$H_0: MSE_i = MSE_j$ vs $H_a: MSE_i < MSE_j$		
Model j/Model i		HTM	LVARX	DLVARX
HTM	0.0023		0.368	0.557
LVARX	**0.0018**	0.632		
DLVARX	0.0024	0.443		

Note: Each panel presents results for a different target variable. In each case, column 1 lists competitor model j, and column 2 presents the Mean Squared Error (MSE) for the model j forecasts. Columns 3-5 list competitor models i and present the p-value for a test of the null hypothesis that $H_0: MSE_i = MSE_j$ versus the alternative hypothesis, $H_a: MSE_i < MSE_j$. Thus, p-values below the conventional 5% significance level in column 3 indicate a rejection of the hypothesis that the MSE of the HTM forecast is equal to its competitor forecast from model j in favor of the alternative that the HTM forecast produces a smaller MSE. The minimum MSE forecast is indicated in bold text, and p-values below the conventional 5% significance level are underlined.

with a statistically lower MSE in three out of four comparisons with the LVARX model and in one out of four comparisons with the DLVARX. In contrast, the DLVARX produces a MSE that is significantly smaller than the HTM only once, while the LVARX model never statistically dominates the HTM despite producing the lowest MSE for the occupancy rate. Interestingly, in the one case where the DLVARX statistically dominates the HTM, the room price forecast, the MSE appear to be almost identical, 0.0007 and 0.0008 respectively. Also, for this case the HTM forecast statistically dominates the LVARX forecast.

Table 8: 8-Step-Ahead Forecast Comparisons 2001:3-2005:1

U.S. Visitor Demand	MSE	$H_0 : MSE_i = MSE_j$ vs $H_a : MSE_i < MSE_j$		
Model j/Model i		HTM	LVARX	DLVARX
HTM	**0.0156**		1.000	0.830
LVARX	0.0432	<u>0.000</u>		
DLVARX	0.0186	0.170		
Japanese Visitor Demand	MSE	$H_0 : MSE_i = MSE_j$ vs $H_a : MSE_i < MSE_j$		
Model j/Model i		HTM	LVARX	DLVARX
HTM	**0.0551**		0.997	0.947
LVARX	0.0854	<u>0.003</u>		
DLVARX	0.1064	0.053		
Room Price– Supply	MSE	$H_0 : MSE_i = MSE_j$ vs $H_a : MSE_i < MSE_j$		
Model j/Model i		HTM	LVARX	DLVARX
HTM	0.0011		0.968	0.461
LVARX	0.0025	<u>0.032</u>		
DLVARX	**0.0010**	0.539		
Occupancy Rate	MSE	$H_0 : MSE_i = MSE_j$ vs $H_a : MSE_i < MSE_j$		
Model j/Model i		HTM	LVARX	DLVARX
HTM	**0.0028**		0.999	1.000
LVARX	0.0059	<u>0.000</u>		
DLVARX	0.0071	<u>0.000</u>		

Note: Each panel presents results for a different target variable. In each case, column 1 lists competitor model j, and column 2 presents the Mean Squared Error (MSE) for the model j forecasts. Columns 3-5 list competitor models i and present the p-value for a test of the null hypothesis that $H_0 : MSE_i = MSE_j$ versus the alternative hypothesis, $H_a : MSE_i < MSE_j$. Thus, p-values below the conventional 5% significance level in column 3 indicate a rejection of the hypothesis that the MSE of the HTM forecast is equal to its competitor forecast from model j in favor of the alternative that the HTM forecast produces a smaller MSE. The minimum MSE forecast is indicated in bold text, and p-values below the conventional 5% significance level are underlined.

When forecasting over a bit longer horizon, the HTM produces the lowest MSE for both visitor demand variables as well as the occupancy rate. While the DLVARX model scores the lowest MSE for hotel room price, its MSE is again only 0.0001 smaller than that of the HTM, a difference that is not statistically significant for the smaller sample of eight-step-ahead forecasts. In fact, the HTM statistically dominates it competitors in five out of eight comparisons at the 5% marginal significance level. In no case does the HTM produce MSEs statistically larger than those of its rivals. The same basic conclusion holds when evaluating the relatively short sample (four forecasts) of twelve-step-ahead forecasts. Again, the HTM produces forecasts with the smallest MSE for all variables except the room price, and statistically lower MSE in six out of eight comparisons. In only one case does a competitor model produce a significantly more accurate forecast; the DLVARX model again produces the best forecast for the hotel room price.

While the HTM, with its focus on the long-run equilibrium, dominates its competitors at the eight- and twelve-step-ahead forecast horizons, it is interesting to note the dominance of the DLVARX model for the case of the hotel room price. For this variable, the PcGETS algorithm selected an extremely parsimonious model that makes the growth of the room price a function of only the growth of U.S. consumer prices. Yet in the identification of the HTM, U.S. consumer prices were tested out of the estimated equilibrium room price relationship, although they do enter in growth rates in the dynamic specification. It may be fruitful to reconsider the room price equilibrium in future work.

Table 9: 12-Step-Ahead Forecast Comparisons 2001:3-2005:1

U.S. Visitor Demand	MSE	$H_0 : MSE_i = MSE_j$ vs $H_a : MSE_i < MSE_j$		
Model j/Model i		HTM	LVARX	DLVARX
HTM	**0.0356**		1.000	0.966
LVARX	0.0566	<u>0.000</u>		
DLVARX	0.0433	<u>0.034</u>		

Japanese Visitor Demand	MSE	$H_0 : MSE_i = MSE_j$ vs $H_a : MSE_i < MSE_j$		
Model j/Model i		HTM	LVARX	DLVARX
HTM	**0.0266**		1.000	1.000
LVARX	0.0551	<u>0.000</u>		
DLVARX	0.1356	<u>0.000</u>		

Room Price– Supply	MSE	$H_0 : MSE_i = MSE_j$ vs $H_a : MSE_i < MSE_j$		
Model j/Model i		HTM	LVARX	DLVARX
HTM	0.0032		0.455	<u>0.038</u>
LVARX	0.0031	0.545		
DLVARX	**0.0012**	0.962		

Occupancy Rate	MSE	$H_0 : MSE_i = MSE_j$ vs $H_a : MSE_i < MSE_j$		
Model j/Model i		HTM	LVARX	DLVARX
HTM	**0.0022**		1.000	1.000
LVARX	0.0085	<u>0.000</u>		
DLVARX	0.0111	<u>0.000</u>		

Note: Each panel presents results for a different target variable. In each case, column 1 lists competitor model j, and column 2 presents the Mean Squared Error (MSE) for the model j forecasts. Columns 3-5 list competitor models i and present the p-value for a test of the null hypothesis that $H_0 : MSE_i = MSE_j$ versus the alternative hypothesis, $H_a : MSE_i < MSE_j$. Thus, p-values below the conventional 5% significance level in column 3 indicate a rejection of the hypothesis that the MSE of the HTM forecast is equal to its competitor forecast from model j in favor of the alternative that the HTM forecast produces a smaller MSE. The minimum MSE forecast is indicated in bold text, and p-values below the conventional 5% significance level are underlined.

6 Concluding Remarks

Cointegration analysis and error-correction modeling have become standard components of the economic modeling and forecasting toolkit. However, the application of these tools in a system setting introduces challenges, including identifying economically meaningful structural relationships, and choosing an appropriate strategy for model reduction. These problems are particularly challenging given the limited data samples often available in practice.

In this paper, we apply Hall et al.'s (2002) theory-directed sequential reduction method to select a vector error correction model (VECM) for forecasting Hawaii tourism. We test and impose theory based weak exogeneity assumptions at the earliest stage in the model reduction process. By doing so, the number of parameters to be estimated is greatly reduced, saving degrees of freedom and improving the efficiency of estimated coefficients.

To our knowledge, ours is the first paper in the empirical tourism literature to tackle the important problem of identifying both supply and demand relationships in a cointegrated system. The theory-guided approach has intuitive appeal and we identify economically meaningful cointegrating vectors. For tourism activities in Hawaii, the paper identifies one demand relationship each for U.S. and Japanese visitors and an inverse supply curve for average hotel room prices. By formally incorporating the supply side, the Hawaii tourism model is less vulnerable to endogeneity biases caused by neglecting demand and supply interactions.

We perform out of sample forecast comparisons against two competing VARs identified automatically (one equation at a time) using the model selection algorithm in PcGETS 10.3 (Hendry and Krolzig, 2001). Based on Diebold and Mariano (1995) tests for forecast accuracy, the HTM dominates out-of-sample forecast comparisons at the eight- and twelve-step ahead forecast horizons. The methodology would appear to be a promising approach for other modeling and forecasting tasks where there are important sources of endogeneity and where available data samples are limited.

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