Modeling 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, the identification of structural relationships is often problematic. Using a theory-directed sequential reduction method suggested by Hall, Henry and Greenslade [Hall, S. G., Henry, S., & Greenslade, J. (2002). On the identification of cointegrated systems in small samples: A modelling strategy with an application to UK wages and prices. \textit{Journal of Economic Dynamics and Control}, 26, 1517–1537], we estimate a vector error correction model of Hawaii tourism, where both demand and supply-side influences are important. We identify reasonable long-run equilibrium relationships, and Diebold–Mariano tests for forecast accuracy demonstrate satisfactory forecasting performance.

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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.\textsuperscript{3}

However, system methods introduce additional challenges, chief among them being 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

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\textsuperscript{3} See Banerjee, Dolado, Galbraith, and Hendry (1993) for a discussion of finite sample endogeneity bias in error correction models.
popular Johansen (1988, 1991, 1995) method uses a statistical approach to achieve the needed restrictions. Pesaran and Shin (2001) and Pesaran and Smith (1998) criticize this approach as a pure mathematical convenience, and instead advocate a theory-based approach. Hall, Henry, and Greenslade (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 structural econometric model of Hawaii tourism, where both demand and supply-side influences may be important.

There exists a large body of empirical literature on modeling and forecasting tourism flows. Nearly all existing studies focus solely on the demand side of the market, attempting to model either the demand arising from alternative source-country markets for a particular tourism destination, or the allocation of outbound travel demand to alternative destinations. The application of cointegration analysis and the associated error-correction dynamic specifications to tourism demand modeling began in the mid-1990s, and is now relatively common. In many cases, single-equation methods have been used with little or no consideration of potential endogeneity problems (see for example Gonzalez & Moral, 1995; Kim & Song, 1998; Song, Romilly, & Liu, 2000; Vogt & Wittayakorn, 1998). When system approaches are used (for example Dritsakis, 2004; Gangnes & Bonham, 1998; Kulendran & King, 1997; Kulendran & Witt, 2001, 2003; Lim & McAleer, 2001; Song & Witt, 2003), identification is obtained exclusively using Johansen’s reduced rank regression technique, and identified cointegrating relationships are often simply assumed to represent demand functions.\(^4\)

\[^4\] There are a number of comprehensive reviews of tourism demand modeling and forecasting, including Crouch (1994a,b), Li, Song, and Witt (2005), Lim (1997, 1999), Song and Li (2008) and Witt and Witt (1992, 1995). Methodology overviews include Archer (1994) and Frechtling (2001).

The identification problem in tourism systems has been noted by some researchers and addressed in various ways, none of which are fully satisfactory. For example, Song and Witt (2003) note the difficulty of interpreting multiple cointegrating relationships, and omit from consideration cases where more than one relationship is found. Citing Kulendran and Witt (2001), Muscatelli and Hurn (1992) select vectors for which the estimated parameters conform to demand theory. Without testing, De Mello and Nell (2005) impose identifying restrictions implied by the AIDS model.

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

The organization of the paper is as follows. Section 2 derives the visitor demand and room price 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. Tourism model specification

There is a relatively small body of theoretical literature on tourism economics, and no single unifying conceptual framework. Some early perspectives...
are reflected by Gray (1970) and Quandt (1970), Bull (1995), Sinclair and Stabler (1997), and Vanhove (2005) provide textbook overviews of tourism theory. In recent years, we have begun to see the development of optimization-based models of aspects of the tourism industry, often directed toward the question of optimal taxation of tourist spending (see for example Copeland, 1989, 1990; Gooroochurn, 2004; Lu, Chang, & Hu, 2008; Morely, 1992; Piga, 2006; Taylor, 1995). While theoretical work remains relatively sparse, we have noted above that there exists a large and well-defined body of empirical literature that can be used to guide the specification of visitor demand equations. Literature on the supply-side of the industry and pricing behavior is much more limited.

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 the tourism product can be expressed as,

\[ D_{ij} = F(Y_i, P_i, P_j, P_j^S, Z), \]  

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 the tourism product in destination country \( j \); \( P_j^S \) is the price of tourism product in competing destinations; and \( Z \) 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,

\[ D_{ij} = F \left( \frac{Y_i}{P_i}, \frac{P_j}{P_i}, \frac{P_j^S}{P_i}, Z \right). \]  

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 & Harrison, 1984). Of the 81 tourism demand studies reviewed by Li et al. (2005), nearly 70% choose the number of visitor arrivals as the measure of demand, while 35% use expenditures or expenditure shares. (These total to more than 100% because some studies include more than one measure.) Visitor arrivals continue to be the most popular measure in studies completed since 2000 (Song & Li, 2008).

Proxies for demand determinants vary considerably, but often include measures of income, relative prices, substitute prices, travel costs, exchange rates, deterministic trends, and dummy variables for one-time events (Li et al., 2005). Typical income measures include gross domestic product, gross national product, national disposable income, personal income, and consumption expenditures, measured in either real, nominal, aggregate, or \( per \ text{ capita} \) form, depending on data availability and the nature of the tourism demand being modeled.\(^6\)

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.\(^7\) Second are measures of substitute prices. Because domestic travel may substitute for foreign travel, aggregate prices

\(^6\) 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, Eqs. (1) and (2) make it clear that both are acceptable, provided that prices are specified accordingly. A \( per \ text{ capita} \) 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.

\(^7\) 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 & Witt, 2000). Occasionally tourism-specific prices are employed. For example, Gangnes and Bonham (1998) use the hotel room price. Others (Edwards, 1995; Martin & Witt, 1987; Witt & Witt, 1992) argue against the use of tourism-specific indices because their coverage may be suspect, and there is little evidence of superior performance.
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 costs of substitute destinations. Exchange rate adjusted relative prices (real exchange rates) are commonly used as proxies for both effects. Finally, transportation costs are sometimes included as a separate factor in determining travel. Many studies augment income and price variables with deterministic effects: time trends to capture evolving consumer tastes; a constant term to account for “utility image” that does not vary greatly with time; dummies to account for various one-off events such as 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, Schultz, & Valerio, 1992; Kliman, 1981; Mak, Moncur, & Yonamine, 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 the demand relationship for each of the two primary Hawaii tourism markets, US and Japanese visitors. Tourists from these two markets consistently account for over 85% of all visitors. To keep the model size manageable, we do not include visitors from other destinations. For the same reason, we include only the principle determinants of tourism demand, leaving out influences that are deemed less central to our analysis. In addition, some conceptually relevant factors are excluded because of the difficulty of finding appropriate proxies. The model includes five demand determinants: US real personal income (yr_us), US 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 a quarterly frequency and are expressed as natural logarithms, with the exception of the occupancy rate, which is expressed as a percentage.

2.2. Tourism supply and pricing behavior

Both theoretical and empirical research on the supply side of tourism markets is scant (Crouch, 1994b; Dwyer & Forsyth, 2006). In much of the empirical tourism literature, supply is assumed to be perfectly elastic, and the 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. Satisfactorily accounting for supply responses is therefore indispensable in deriving unbiased demand 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 and services that 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 also because it is possible to obtain reliable data on hotel room prices. Visitor accommodations are structure intensive; that is, they have high fixed costs relative

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8 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 & Song, 1998; Song et al., 2000) include real exchange rates from a number of competing countries, while others (Vogt & Wittayakorn, 1998) use a single weighted real exchange rate. Some authors (Lathiras & Siriopoulos, 1998; Vogt & 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.

9 Song and Witt (2000) suggest using “representative air fares between origin and destination for air travel,” as in Crouch (1991) and Fujii, Khaled, and Mak (1985). Gangnes and Bonham (1998) reject such a 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 data limitations, Li et al. (2005) report that only about 30% of recent tourism demand models included a measure of travel cost.

10 This point is also made by Li et al. (2005) and Sinclair and Stabler (1997).

11 The difficulty defining tourism supply is discussed by Sinclair and Stabler (1997) and Smith (1998). This issue has been a key challenge in the development of an international system of tourism satellite accounts (United Nations Statistics Division, 2008).

12 Visitors to Hawaii have spent an average of 33% of total expenditures on hotel lodging services over the past three decades.
Table 1
Summary of variables in the Hawaii tourism model.

<table>
<thead>
<tr>
<th>Mnemonic</th>
<th>Description</th>
<th>Units</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Hawaii variables</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>vus</td>
<td>US visitors to Hawaii</td>
<td>thou</td>
<td>DBEDT</td>
</tr>
<tr>
<td>vjp</td>
<td>Japanese visitors to Hawaii</td>
<td>thou</td>
<td>DBEDT</td>
</tr>
<tr>
<td>prm</td>
<td>Hawaii average daily hotel room rate</td>
<td>dollars</td>
<td>DBEDT</td>
</tr>
<tr>
<td>ocup</td>
<td>Hawaii average daily hotel occupancy rate</td>
<td>%</td>
<td>DBEDT</td>
</tr>
<tr>
<td><strong>US variables</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>yr.us</td>
<td>US real personal income</td>
<td>bil 82–84$</td>
<td>BEA</td>
</tr>
<tr>
<td>cpi.us</td>
<td>US CPI (1982–1984 = 100)</td>
<td>index</td>
<td>BLS</td>
</tr>
<tr>
<td><strong>Japan variables</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>yr.jp</td>
<td>Japan real personal income</td>
<td>bil 95Yen</td>
<td>ESRI</td>
</tr>
<tr>
<td>cpi.jp</td>
<td>Japan CPI (1995 = 100)</td>
<td>index</td>
<td>SBSC</td>
</tr>
<tr>
<td>xr.jp</td>
<td>Yen/dollar exchange rate</td>
<td>Yen/dollar</td>
<td>FED</td>
</tr>
<tr>
<td><strong>Calculated variable</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>cpi.E.jp</td>
<td>cpi.jp/xr.jp</td>
<td>index</td>
<td>Authors’ calc.</td>
</tr>
</tbody>
</table>

Note: Except for the hotel occupancy rate, natural logarithms of each series are used in the analysis.


to operating costs. As a result, in the short run there is a considerable incentive for the hotelier to fill an empty room by discounting the price to almost as low as the negligible marginal cost of filling a room, leading to price incentives during off-peak periods. Over longer horizons, capacity is adjusted through expansion and contraction of room inventory.

One approach to modeling the room supply is to estimate an inverted supply curve. Examples of this appear in the hotel room tax literature (Bonham & Gangnes, 1996; Fujii et al., 1985). The supply price of hotel rooms is assumed to be a mark-up over the marginal cost, $P_R = \text{markup} \cdot MC = M \cdot R(Q_R, P_L, P_K, P_Z)$, (3)

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.

Because the average length of stay and the number of visitors per room are relatively stationary, the number of hotel rooms rented will follow the same trend path as the number of visitors, and therefore visitor arrivals can be taken as a measure of the quantity of rented rooms. Here, for consistency with demand-side modeling, we use the sum of US and Japanese visitors ($vus + vjp$), ignoring the limited number of Hawaii visitors from other markets. The parameter on arrivals is a measure of the (inverse) long-run supply elasticity of lodging services. In the short term, the markup over the marginal cost should be sensitive to excess demand/supply conditions, as suggested above. We include the occupancy rate ($ocup$) as a proxy for these influences. 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 US consumer price index ($cpi.us$) as a rough proxy for cost influences.

3. Empirical methodology

We model Hawaii tourism activity 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 the Vector Error Correction Model (VECM) for an $m \times 1$ vector of I(1) variables, $z_t$, 

$$
\Delta z_t = -\Pi z_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta z_{t-i} + d + \epsilon_t,
$$

where $k$ is the number of lags in the unrestricted VAR representation of $z_t$, and $d$ is an $m$ vector of deterministic terms.\footnote{In addition to an intercept, pulse-type dummy variables are included for the 9/11 terror attacks.} The equilibrium properties of (4) are characterized by the rank of $\Pi$.\footnote{In Eq. (4), $\Pi = I_m - \sum_{i=1}^{k} \Phi_i$, $\Gamma_i = -\sum_{j=i+1}^{k} \Phi_j$, $i = 1, \ldots, k-1$, where $\Phi_i$, $i = 1, 2, \ldots, k$, are $m \times m$ matrices of unknown parameters in the unrestricted VAR representation of $z_t$. We assume that the roots of $|I_m - \Phi_1 \lambda - \Phi_2 \lambda^2 - \cdots - \Phi_k \lambda^k| = 0$ lie either on or outside the unit circle, but rule out the possibility that one or more elements of $\lambda$ are $|I(2)|$. A review of the econometric analysis of I(2) variables is provided by Halkdruk (1998).} If the elements of $\epsilon_t$ are I(1) but not cointegrated, $\Pi$ is rank zero and a VECM to a more parsimonious representation: 

3.1. Testing weak exogeneity

A well known problem with VARs, and one which is 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.

One way to address the over-parameterization problem is to test and impose weak exogeneity assumptions. For each series that is 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 ($yr..ms, yr..jp, cpi..ms, cpi..E..jp$) 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 in the structural modeling of \(y_t\), conditional on its own past values, \(y_{t-1}, y_{t-2}, \ldots\), and the current and past values of \(x_t\). The parameters, matrices, and errors in the VECM equation (4) can be partitioned conformably as \(d = (d_y', d_x')', \alpha = (\alpha_y', \alpha_x')', \Gamma_i = (\Gamma_{yi}, \Gamma_{xi})', i = 1, 2, \ldots, k - 1, \epsilon_t = (\epsilon_{yt}, \epsilon_{xt})',\) and the variance–covariance matrix as

\[
\Omega = \begin{pmatrix}
\Omega_{yy} & \Omega_{yx} \\
\Omega_{xy} & \Omega_{xx}
\end{pmatrix}.
\] (5)

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

\[
\Delta y_t = (d_y - \omega d_x) + \omega \Delta x_t + (\alpha_y - \omega \alpha_x)\beta' z_{t-1} + \sum_{i=1}^{k-1} (\Gamma_{yi} - \omega \Gamma_{xi}) \Delta z_{t-i} + (\epsilon_{yt} - \omega \epsilon_{xt}),
\]

\[
\Delta x_t = d_x + \alpha_x \beta' z_{t-1} + \sum_{i=1}^{k-1} \Gamma_{xi} \Delta z_{t-i} + \epsilon_{xt},
\] (7)

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

The parameters of interest, \(\beta'\), enter both the conditional model (6) and the marginal model (7), and the adjustment coefficients \((\alpha_y - \omega \alpha_x)\) depend on the covariance matrix, \(\Omega\), and all the adjustment coefficients \((\alpha_y, \alpha_x)\). Therefore, the parameters of interest cannot be variation free, and a full system analysis is required. When the parameters of interest are the cointegrating vector \(\beta'\), \(x_t\) is weakly exogenous if and only if \(\alpha_x = 0\) (Johansen, 1991). The condition \(\alpha_x = 0\) causes \(\beta\) to drop out of the marginal distribution for \(x_t\) in Eq. (7), and ensures that \(\alpha_x\) does not appear in the conditional model in Eq. (6).\(^{17}\) Therefore, the conditional model (6) 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, we conduct Johansen rank tests.\(^{18}\) The resulting tests have greater power than tests conducted without the theory-based exogeneity restrictions.

3.2. Restricting cointegrating vectors

Even with a known rank for the long run matrix, \(\Pi\), an identification problem arises because the matrices \(\alpha\) and \(\beta\) are not uniquely identified without additional information. Pesaran and Shin (2001) show that \(r^2\) restrictions (\(r\) restrictions per vector) are needed for exact identification. The most common approach to imposing the \(r^2\) identifying restrictions is Johansen’s statistical approach. Specifically, Johansen’s just identified estimator of \(\beta\) 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.\(^{19}\) They emphasize the use of economic theory to guide the choice of long-run exact- and over-identifying restrictions. The theory-guided approach takes Johansen’s just identified vector \(\beta_j\) 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), 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 are available for the period 1980 to 2005. 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

\(^{17}\) Two conditions must be satisfied for \(x_t\) to be weakly exogenous (Hall et al., 2002). (1) The parameters of interest must be functions of the parameters in the conditional model alone. (2) The parameters in the conditional model and the parameters in the marginal model must be variation-free; that is, they do not have any joint restrictions.

\(^{18}\) The methodology for testing the rank of \(\Pi\) is well known, and is addressed in standard graduate level econometrics texts (see, e.g., Davidson & MacKinnon, 2004); for this reason it will not be covered here.

\(^{19}\) Another non-theoretical method of identification is the triangularization approach of Phillips (1991, 1995).
sample period for initial estimation and identification, avoids the difficult task of modeling the September 11, 2001 (9/11) shock to Hawaii tourism, and preserves a sufficiently large post-estimation period for out-of-sample forecast evaluation.

4.1. Weak exogeneity

We begin with the vector of eight variables, $z_t = (vus, vjp, prm, occup, yr_us, cpi_us, yr_jp, cpi_E_jp)$ discussed in Section 2. We hypothesize that the four tourism variables, $y_t = (vus, vjp, prm, occup)$, 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 most seven cointegrating vectors. 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 weak exogeneity of US real income, $yr_us$, or the exchange-rate-adjusted Japanese price level, $cpi_E_jp$; tests for both variables have marginal significance levels ($p$-values) in excess of 10% (see Table 2, Panel 1). In contrast, weak exogeneity of both the US price level, $cpi_us$, and Japanese real income, $yr_jp$, is strongly rejected at the 1% level.20

While $\alpha_x = 0$ is a necessary and sufficient condition for weak exogeneity of $x_t$ with respect to $\beta$, this condition often proves to be too strong in practice, because exogenous variables may form cointegrating relationships among themselves (Pesaran, Shin, & Smith, 2000). In our case, because of macroeconomic relationships within and between the US 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.22 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, Johansen, Nielsen, and Rahbek (1998). Instead of estimating the whole system and testing whether a subset of $\alpha$ is zero, they suggest estimating the conditional 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.

20 We treat all variables in the HTM as I(1). Zhou, Bonham, and Gangnes (2004) report augmented Dickey Fuller (Dickey & Fuller, 1979, 1981), Perron (1990) and Schwert (1989) 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. (The results of these tests are available from the authors on request.)

21 Because weak exogeneity depends on the 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 variables, and five unrestricted cointegrating vectors, $r = 5$. The test results (not shown) continue to strongly reject the null hypothesis of weak exogeneity of both $cpi_us$ and $yr_jp$ at less than the 1% significance level.

22 Using a restricted trend, unrestricted intercept VAR specification, we cannot reject the hypothesis that there is at least one cointegrating relationship among the four variables.

Table 2
Weak exogeneity tests.

<table>
<thead>
<tr>
<th>Variable</th>
<th>$\chi^2$(7)</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$yr_us$</td>
<td>10.42</td>
<td>0.17</td>
</tr>
<tr>
<td>$cpi_us$</td>
<td>37.67</td>
<td>0.00</td>
</tr>
<tr>
<td>$yr_jp$</td>
<td>31.90</td>
<td>0.00</td>
</tr>
<tr>
<td>$cpi_E_jp$</td>
<td>11.02</td>
<td>0.14</td>
</tr>
</tbody>
</table>

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

Panel 2: Harbo weak exogeneity tests

<table>
<thead>
<tr>
<th>Variable</th>
<th>F-test</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$yr_us$</td>
<td>0.34</td>
<td>0.79</td>
</tr>
<tr>
<td>$cpi_us$</td>
<td>1.21</td>
<td>0.32</td>
</tr>
<tr>
<td>$yr_jp$</td>
<td>2.64</td>
<td>0.06</td>
</tr>
<tr>
<td>$cpi_E_jp$</td>
<td>0.03</td>
<td>0.99</td>
</tr>
</tbody>
</table>

Note: Column 1 lists the variables tested for weak exogeneity. Column 2 presents the $\chi^2$ statistic ($F$ statistic in the case of Panel 2) for the null hypothesis of weak exogeneity. Column 3 presents the marginal significance level of the statistic in Column 2.
Table 3
Cointegration rank tests.

<table>
<thead>
<tr>
<th>H(r)</th>
<th>Trace test</th>
<th>Max eigenvalue test</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Statistic</td>
<td>0.05</td>
</tr>
<tr>
<td>r = 0</td>
<td>139.30</td>
<td>99.11</td>
</tr>
<tr>
<td>r ≤ 1</td>
<td>86.48</td>
<td>69.84</td>
</tr>
<tr>
<td>r ≤ 2</td>
<td>43.68</td>
<td>45.10</td>
</tr>
<tr>
<td>r ≤ 3</td>
<td>19.90</td>
<td>23.17</td>
</tr>
</tbody>
</table>

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

The results from the Harbo test for weak exogeneity are reported in Panel 2 of Table 2 (note that the cointegrating vectors used in these tests are identified in Section 4.3 below). The first differences of the “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 parameters 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 vector representing Japanese visitor demand (9), we normalize on US visitor arrivals, demand by Japanese visitors, and exclude Japanese visitor arrivals (β1, 2) represent the demand for tourism services by US visitors, demand by Japanese visitors, and a pricing rule for Hawaii visitor accommodations. To obtain the just-identified system, we impose r = 3 restrictions per equation reported in Table 4. In the cointegrating vector representing US visitor demand, Eq. (8), we normalize on US visitor arrivals, vus, and exclude Japanese visitor arrivals (β1, 2 = 0) and Japanese real income, (β1, 7 = 0). In the vector representing Japanese visitor demand (9), we normalize on Japanese visitor arrivals, and exclude US visitor arrivals (β2, 1 = 0) and US real income (β2, 5 = 0). Finally, for the supply vector (10) we normalize on the hotel room price, and exclude both US and Japanese income (β3, 5, β3, 7 = 0). Parameter

4.2. Cointegrating rank

Imposing the weak exogeneity restrictions tested above, we proceed to test the rank of the long run matrix, , 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 vectors 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 for three cointegrating relationships, and our objective of modeling one supply and two demand relationships, we proceed under the assumption that the system has three cointegrating vectors.

4.3. Long-run cointegrating vectors

Our goal here is to identify three long run equilibrium relationships, β′z_{t-1}, where β′ is the 3 x 9 matrix of unrestricted cointegrating parameters. We test theory-driven restrictions under the assumption that the three cointegrating vectors (β1, β2, and β3) represent the demand for tourism services by US visitors, demand by Japanese visitors, and a pricing rule for Hawaii visitor accommodations. To obtain the just-identified system, we impose r = 3 restrictions per equation reported in Table 4. In the cointegrating vector representing US visitor demand, Eq. (8), we normalize on US visitor arrivals, vus, and exclude Japanese visitor arrivals (β1,2 = 0) and Japanese real income, (β1,7 = 0). In the vector representing Japanese visitor demand (9), we normalize on Japanese visitor arrivals, and exclude US visitor arrivals (β2,1 = 0) and US real income (β2,5 = 0). Finally, for the supply vector (10) we normalize on the hotel room price, and exclude both US and Japanese income (β3,5, β3,7 = 0). Parameter

23 Following Pesaran et al. (2000), we allow for an unrestricted intercept in the VECM (4) and restrict the 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.
Table 5

<table>
<thead>
<tr>
<th>Country</th>
<th>Demand Equation</th>
<th>Coefficients</th>
<th>Standard Errors</th>
<th>t-values</th>
</tr>
</thead>
<tbody>
<tr>
<td>US</td>
<td>US visitor demand</td>
<td>( v_{us} = \beta_{1,3} \cdot \text{prm} + \beta_{1,4} \cdot \text{ocup} + \beta_{1,5} \cdot \text{yr}<em>{us} + \beta</em>{1,6} \cdot \text{cpi}<em>{us} + \beta</em>{1,8} \cdot \text{cpi}<em>{E,jp} + \beta</em>{1,9} \cdot t + \xi_{Dus} )</td>
<td>(-9.58, -4.19, 25.89, 16.44, 0.46, -0.19)</td>
<td>(-2.70, -4.52, 7.26, 8.66, 0.73, 0.09)</td>
</tr>
<tr>
<td>Japan</td>
<td>Japanese visitor demand</td>
<td>( v_{jp} = \beta_{2,3} \cdot \text{prm} + \beta_{2,4} \cdot \text{ocup} + \beta_{2,5} \cdot \text{cpi}<em>{us} + \beta</em>{2,7} \cdot \text{yr}<em>{jp} + \beta</em>{2,8} \cdot \text{cpi}<em>{E,jp} + \beta</em>{2,9} \cdot t + \xi_{Djp} )</td>
<td>(-1.83, 1.70, -3.04, 4.82, 0.02, 0.03)</td>
<td>(0.44, 0.60, 1.15, 0.89, 0.12, 0.01)</td>
</tr>
</tbody>
</table>

Accommodations pricing

\( \text{prm} = \beta_{3,1} \cdot v_{us} + \beta_{3,2} \cdot v_{jp} + \beta_{3,4} \cdot \text{ocup} + \beta_{3,5} \cdot \text{cpi}_{us} + \beta_{3,8} \cdot \text{cpi}_{E,jp} + \beta_{3,9} \cdot t + \xi_{S} \) (10)

<table>
<thead>
<tr>
<th>Country</th>
<th>Coefficients</th>
<th>Standard Errors</th>
<th>t-values</th>
</tr>
</thead>
<tbody>
<tr>
<td>US</td>
<td>( \beta_{3,1} )</td>
<td>0.44</td>
<td>(0.11)</td>
</tr>
<tr>
<td></td>
<td>( \beta_{3,2} )</td>
<td>0.43</td>
<td>(0.46)</td>
</tr>
<tr>
<td></td>
<td>( \beta_{3,3} )</td>
<td>1.89</td>
<td>(0.59)</td>
</tr>
<tr>
<td></td>
<td>( \beta_{3,4} )</td>
<td>-0.24</td>
<td>(0.09)</td>
</tr>
<tr>
<td></td>
<td>( \beta_{3,5} )</td>
<td>-0.26</td>
<td>(0.00)</td>
</tr>
<tr>
<td>Japan</td>
<td>( \beta_{3,6} )</td>
<td>0.01</td>
<td>(0.00)</td>
</tr>
</tbody>
</table>

log likelihood = 1288.23

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

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

4.3.1. US tourism demand

To identify a US tourism demand relationship, we test four over-identifying restrictions. We test exclusion restrictions on the occupancy rate, \( \text{ocup} \), and Japanese consumer prices, \( \text{cpi}_{E,jp} \); a homogeneity restriction on the hotel room price, \( \text{prm} \), and the US consumer price index, \( \text{cpi}_{us} \); a restriction on the hotel room price elasticity of \( \beta_{1,3} = -\beta_{1,6} \); and a restriction on the magnitude of the US income elasticity. Note that the income elasticity in the just-identified US 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 US real income elasticity (\( \beta_{1,5} \)) 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.

The 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’s (1993) 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, ranging from \(-7.3\) to 1.6 for destination prices, and from \(-7.6\) to 4.1 for exchange rates. The resulting US demand relationship is presented in Table 5.

4.3.2. Japanese tourism demand

To identify a Japanese tourism demand equation, we test four over-identifying restrictions similar to those used for US tourism demand. We test exclusion restrictions on the hotel occupancy rate, \( \text{ocup} \), US consumer prices, \( \text{cpi}_{us} \), and the time trend. In addition, we test one homogeneity restriction on the hotel room price and Japanese prices, \( \text{prm} \) and \( \text{cpi}_{E,jp} \), \( \beta_{2,3} = -\beta_{2,8} \). The Japanese income elasticity is left unrestricted, as there is no clear indication in the literature of a consensus estimate, and the estimated elasticity is an economically reasonable 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.

4.3.3. Accommodations pricing (supply)

To identify a room pricing relationship for visitor accommodations, we test two over-identifying restrictions; we exclude both the US and Japanese price levels (\( \text{cpi}_{us} \) and \( \text{cpi}_{E,jp} \)). While we have eliminated any possible proxy for production costs, 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 US travelers to the 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 US travel to Canada, Europe and Mexico; Canadian tourism to the US and other countries; and US destination tourism by major foreign countries. She finds a large range of income elasticities (from \(-0.15\) to 6.6), with a median of 2.2.
Table 5
Over-identified system.

US visitor demand

\[ v_{us} = \beta_{1,3} \cdot prm + \beta_{1,4} \cdot ocup + \beta_{1,5} \cdot yr_{us} + \beta_{1,6} \cdot cpi_{us} \\
+ \beta_{1,8} \cdot cpi_{jp} + \beta_{1,9} \cdot t + \xi_{Dus} \]  

(8)

<table>
<thead>
<tr>
<th>( \beta_{1,3} )</th>
<th>( \beta_{1,4} )</th>
<th>( \beta_{1,5} )</th>
<th>( \beta_{1,6} )</th>
<th>( \beta_{1,8} )</th>
<th>( \beta_{1,9} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>-0.55</td>
<td>0</td>
<td>3.5</td>
<td>0.55</td>
<td>0</td>
<td>-0.02</td>
</tr>
<tr>
<td>(-0.31)</td>
<td>(0.0)</td>
<td>(0.31)</td>
<td>-</td>
<td>(0.00)</td>
<td></td>
</tr>
</tbody>
</table>

Japanese visitor demand

\[ v_{jp} = \beta_{2,3} \cdot prm + \beta_{2,4} \cdot ocup + \beta_{2,6} \cdot cpi_{us} + \beta_{2,7} \cdot yr_{jp} \\
+ \beta_{2,8} \cdot cpi_{jp} + \beta_{2,9} \cdot t + \xi_{Djp} \]  

(9)

<table>
<thead>
<tr>
<th>( \beta_{2,3} )</th>
<th>( \beta_{2,4} )</th>
<th>( \beta_{2,6} )</th>
<th>( \beta_{2,7} )</th>
<th>( \beta_{2,8} )</th>
<th>( \beta_{2,9} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>-0.37</td>
<td>0</td>
<td>2.23</td>
<td>0.37</td>
<td>0</td>
<td>-</td>
</tr>
<tr>
<td>(-0.09)</td>
<td>(0.13)</td>
<td>(0.09)</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

Accommodations pricing

\[ prm = \beta_{3,1} \cdot v_{us} + \beta_{3,2} \cdot v_{jp} + \beta_{3,4} \cdot ocup + \beta_{3,6} \cdot cpi_{us} \\
+ \beta_{3,8} \cdot cpi_{jp} + \beta_{3,9} \cdot t + \xi_{S} \]  

(10)

<table>
<thead>
<tr>
<th>( \beta_{3,1} )</th>
<th>( \beta_{3,2} )</th>
<th>( \beta_{3,4} )</th>
<th>( \beta_{3,6} )</th>
<th>( \beta_{3,8} )</th>
<th>( \beta_{3,9} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.54</td>
<td>0.13</td>
<td>1.83</td>
<td>0</td>
<td>0</td>
<td>0.01</td>
</tr>
<tr>
<td>(0.10)</td>
<td>(0.07)</td>
<td>(0.42)</td>
<td>-</td>
<td>-</td>
<td>(0.00)</td>
</tr>
</tbody>
</table>

Note: Each column presents parameter estimates, with 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 levels for this test are in brackets. Computations are carried out using Pc-Fiml 9.10.

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 \( \Delta v_{us} \), \( \Delta v_{jp} \), \( \Delta prm \), and \( \Delta ocup \), respectively. All equations pass all diagnostic tests at the 5% significance level. The existence of long-run equilibrium error terms in the model equations allows for a temporary disequilibrium between causal variables and the demand and supply variables. The adjustment factors (\( \alpha \)'s) capture the speed of adjustment toward the equilibrium relationship. For example, if US arrivals are less than predicted by US 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 US visitor growth, \( \Delta v_{us} \), contains both \( \xi_{Dus} \) and \( \xi_{S} \). The loading parameter on the US demand equilibrium error, \( \xi_{Dus} \), is -0.11, so 11% of the equilibrium error is corrected each period. In the equation for Japanese visitor growth, \( \Delta v_{jp} \), the equilibrium error associated with Japanese visitor demand, \( \xi_{Djp} \), enters with a coefficient of -0.34, implying a complete adjustment towards equilibrium in slightly less than three quarters. The equilibrium errors for US demand, \( \xi_{Dus} \), and the pricing rule, \( \xi_{S} \), enter the hotel room price equation, \( \Delta prm \), while all three 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 pricing rule, \( \xi_{S} \), is retained, despite the

4.4. The dynamic model

At this stage, the dynamics are simplified by dropping the statistically insignificant terms from Eqs. (8)–(10). 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 \( \chi^2 \) statistic of 30.75, with a \( p \)-value of 0.99. We do not reject these exclusion restrictions at the 1% level. The estimated loading parameters and corresponding diagnostic test statistics are shown in Table 6.

both the occupancy rate and the number of visitors have the expected 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 US 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 pricing equation is presented in Table 5.

Taken as a group, we cannot reject these over-identifying restrictions at the 5% level. The likelihood ratio statistic for the joint test of all over-identifying restrictions has a value of 18, and a marginal significance level of 5.5%. (The relatively low significance level is primarily a result of the large magnitude of the restriction on the US 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.
Table 6
Dynamic model: Loading parameters and diagnostics.

<table>
<thead>
<tr>
<th>Equation</th>
<th>$\alpha_1$</th>
<th>$\alpha_2$</th>
<th>$\alpha_3$</th>
<th>$R^2$</th>
<th>AR1-F</th>
<th>Normality</th>
<th>Arch</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta vus$</td>
<td>-0.11</td>
<td>0.33</td>
<td>0.51</td>
<td>2.25</td>
<td>2.05</td>
<td>0.32</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-5.18)</td>
<td>(5.04)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\Delta vjp$</td>
<td>-0.34</td>
<td>-0.13</td>
<td>0.62</td>
<td>2.32</td>
<td>1.68</td>
<td>0.19</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-4.57)</td>
<td>(-1.57)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\Delta prm$</td>
<td>-0.09</td>
<td>-0.16</td>
<td>0.46</td>
<td>2.15</td>
<td>0.83</td>
<td>1.06</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-5.06)</td>
<td>(-4.43)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\Delta ocup$</td>
<td>-0.02</td>
<td>-0.10</td>
<td>0.22</td>
<td>0.65</td>
<td>2.21</td>
<td>1.25</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-1.25)</td>
<td>(-3.59)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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

Note: Column 1 lists the dependent variable for each equation in the system; Columns 2–4 give the loading parameters, $\alpha_1$–$\alpha_3$, and the corresponding Student $t$-statistics for the three identified cointegrating vectors; Column 5 presents the coefficient of determination $R^2$; Column 6 gives the $F$-test results (and corresponding $p$-values) for the null hypothesis that the equation residuals are independent up to lag 5. Column 7 contains the results of a $\chi^2$ test (with $p$-values) 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 parentheses (.) are the Student $t$-statistics corresponding to the loading parameters, whereas those in square brackets [.] are $p$-values for individual tests. All computations are carried out using Pc-Fiml 9.10, with the exception of the $R^2$ values, which are calculated using RATS v 5.0.

fact that its $t$-value ($-1.57$) is below the 5% critical value. The same is true for the US 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 5) in the equation residuals. To more fully evaluate the performance of the HTM, we perform an out of sample forecast evaluation below.

5. Forecast evaluation

This section evaluates the forecasting performance of the newly identified HTM. To preserve data for an 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 terrorist 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 Iraq War, 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.\footnote{See Bonham, Edmonds, and Mak (2006) for an analysis of the impact of 9/11 and other shocks on US and Hawaii tourism.}

We compare forecasts from the HTM with those from three rival models. Two 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. The DLVARX in differences precludes the possibility of cointegration, but 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 & Krolzig, 2001).\footnote{See Krolzig (2003) for an evaluation of the use of the PcGETS algorithms to identify structural VARs.} Specifically, we construct a Generalized Unrestricted Model (GUM) in log levels (or differences) for each endogenous variable in the HTM just-identified system. That 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.\textsuperscript{27} 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.”

The third competing model is a system of Autoregressive Integrated Moving Average (ARIMA) models selected automatically, based on an algorithm suggested by Hannan and Rissanen (1982).\textsuperscript{28} The HR approach selects the ARIMA\((p, 1, q)\) model that minimizes the residual variance, with a penalty for higher autoregressive and moving average orders, \(p\) and \(q\).

While it is common in the forecasting literature, both generic and tourism specific, to compare model forecasts with a naive no change or random walk forecast, it is important to note that both the GETS and ARIMA model selection algorithms can chose the random walk specification. In fact, minimizing the HR criterion results in an ARIMA\((0, 1, 0)\) – random walk – model being selected for the hotel room price.

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.\textsuperscript{29} We obtain 12 four-step-ahead, 8 eight-step-ahead and 4 twelve-step-ahead dynamic forecasts.

Rather than simply rank the rival models based on loss functions such as the 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 Harvey, Leybourne, and Newbold (1998) modification of the Diebold and Mariano (1995) test.

We construct pairwise rankings between the HTM and its three competitor models for each endogenous variable: US visitor arrivals, Japanese visitor arrivals, the hotel room price, and the occupancy rate. Tables 7–9 present MAPE and MSE rankings, along with Diebold and Mariano (DM) test results, for the four-, eight-, and twelve-step-ahead forecasts respectively. The second column of Tables 7–9, labeled HTM, shows the \(p\)-values for the DM test of the null hypothesis that the HTM model forecast is equal in accuracy to its competitor (listed in Column 1), versus the alternative hypothesis that the HTM forecast has a lower MSE. Tests with the opposite alternative hypothesis are presented in the row labeled HTM. That is, the null hypothesis is that the HTM model forecast produces the same MSE as its competitor, and the alternative hypothesis is that the competitor MSE is lower. For all tests, \(p\)-values below 5\% are underlined.

For the relatively short-term four-step-ahead forecasts, the HTM produces forecasts with a statistically lower MSE for three out of four comparisons with the LVARX model, one out of four comparisons with the DLVARX, and two of four comparisons with the ARIMA model forecasts. In contrast, the DLVARX and ARIMA forecasts produce MSEs that are significantly smaller than the HTM only once each, while the LVARX model never statistically dominates the HTM.

The results are much the same when forecasting over longer horizons. For the sample of eight-step-ahead forecasts, the HTM forecasts statistically dominate the LVARX forecasts in three out of four comparisons, the DLVARX forecasts once, and the ARIMA forecasts twice. In only one case, the ARIMA model forecast of the occupancy rate, does a competitor forecast result in a MSE statistically smaller than the HTM forecasts. The same basic conclusion holds when evaluating the relatively small sample (four forecasts) of twelve-step-ahead forecasts. The HTM produces forecasts with MSEs that are statistically smaller than those of the LVARX and DLVARX forecasts in three of four cases, and statistically dominate the ARIMA forecasts in two of three cases. The DLVARX model again produces the best forecast for the hotel room price, and the ARIMA forecasts are statistically more accurate than the HTM in two cases.

\textsuperscript{27} As for the HTM, we also include dummy variables for the 1985 United Airlines strike and the 1991 Persian Gulf War.

\textsuperscript{28} For a detailed discussion and applications of the identification procedure employed here, see Granger and Newbold (1986) and Hannan and McDougall (1988).

\textsuperscript{29} All models are re-estimated, but not re-selected, once every four quarters. Estimation results are not reported here, but are available upon request.
In summary, the HTM model produced statistically more accurate forecasts than the LVARX, DLVARX, and ARIMA models in 83%, 42%, and 50% of the comparisons. The same three models produced statistically more accurate forecasts than the HTM model in 0%, 17%, and 30% of the comparisons. Much of the literature that has examined the accuracy of tourism forecasting models has found that sophisticated methods, including error correction models, often produce forecasts which are no better than or inferior to those from relatively simple ARIMA models.\footnote{For example, Gonzalez and Moral (1995) and Kulendran and King (1997) find that ECM forecasts are dominated by ARIMA forecasts. However, Kulendran and Witt (2001) find that it is possible to identify an ARIMA model that is not outperformed by an ECM.} In the case of the HTM, based on formal tests of accuracy, we find that the HTM routinely outperforms other VARX competitors and has a slight advantage over its ARIMA competitor. In forecasting both Japanese visitor arrivals and room prices, the HTM dominates the ARIMA model at each forecast horizon, while the ARIMA model dominates the HTM for all forecasts of the occupancy rate. The relatively good performance of the VECM model suggests that the methodology warrants further study.

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
Table 8

\[
\begin{array}{cccccc}
\text{Model } j & H_0 : \text{MSE}_i = \text{MSE}_j & \text{vs} & H_a : \text{MSE}_i < \text{MSE}_j & \text{MSE} & \text{MAPE} \\
\hline
\text{US visitors} & & & & & \\
HTM & 1.000 & 0.830 & 0.190 & 0.0156 & 0.01583 \\
LVARX & 0.000 & 0.0432 & 0.02794 & 0.0186 & 0.01813 \\
DLVARX & 0.170 & 0.0186 & 0.01813 & 0.0146 & 0.01604 \\
ARIMA(3, 1, 2) & 0.810 & 0.0156 & 0.01583 & 0.0186 & 0.01813 \\
\hline
\text{JP visitors} & & & & & \\
HTM & 0.997 & 0.947 & 1.000 & 0.0551 & 0.03644 \\
LVARX & 0.003 & 0.0854 & 0.0447 & 0.0164 & 0.0387 \\
DLVARX & 0.053 & 0.1064 & 0.0387 & 0.1587 & 0.0659 \\
ARIMA(0, 1, 1) & 0.000 & 0.1587 & 0.0659 & 0.0185 & 0.0271 \\
\hline
\text{Room price} & & & & & \\
HTM & 0.968 & 0.461 & 1.000 & 0.0011 & 0.0049 \\
LVARX & 0.032 & 0.0025 & 0.0084 & 0.0010 & 0.0043 \\
DLVARX & 0.539 & 0.0010 & 0.0043 & 0.0185 & 0.0271 \\
ARIMA(0, 1, 0) & 0.000 & 0.0185 & 0.0271 & 0.0009 & 0.0307 \\
\hline
\text{Occupancy} & & & & & \\
HTM & 0.999 & 1.000 & 0.006 & 0.0028 & 0.0607 \\
LVARX & 0.000 & 0.0059 & 0.08904 & 0.0071 & 0.1049 \\
DLVARX & 0.000 & 0.0071 & 0.1049 & 0.0009 & 0.0307 \\
ARIMA(2, 1, 3) & 0.994 & 0.0009 & 0.0307 & 0.0009 & 0.0307 \\
\end{array}
\]

Note: Each panel presents results for a different target variable. In each case, column 1 lists competitor model \( j \), and columns 6–7 present the Mean Squared Error (MSE) and Mean Absolute Percentage Error (MAPE) for the model \( j \) forecasts. Columns 2–5 list competitor models \( i \) and present the \( p \)-values for a test of the null hypothesis that \( H_0 : \text{MSE}_i = \text{MSE}_j \) versus the alternative hypothesis, \( H_a : \text{MSE}_i < \text{MSE}_j \). Thus, \( p \)-values below the conventional 5% significance level in column 2 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. For each forecast target, the minimum MSE and MAPE are underlined, as are \( p \)-values below the conventional 5% significance level.

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 the estimated coefficients.

To our knowledge, ours is the first paper in the empirical tourism literature to tackle the important problem of identifying both demand- and supply-side 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 US 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 which were identified automatically (one equation at a time) using the model selection algorithm in PcGETS 10.3 (Hendry & Krolzig, 2001), as well as an ARIMA alternative. Based on the Diebold and Mariano (1995) tests for forecast accuracy, the HTM routinely outperforms other VARX competitors, but has an advantage over its ARIMA competitor in fewer cases. The failure to consistently outperform simple ARIMA models is
Table 9

<table>
<thead>
<tr>
<th>Model</th>
<th>( H_0 ): MSE(_i) = MSE(_j) vs. ( H_a ): MSE(_i) &lt; MSE(_j)</th>
<th>MSE</th>
<th>MAPE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model ( j )</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>HTM</td>
<td></td>
<td></td>
</tr>
<tr>
<td>US visitors</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HTM</td>
<td>1.000</td>
<td>0.033</td>
<td>0.0356</td>
</tr>
<tr>
<td>LVARX</td>
<td>0.000</td>
<td>0.0566</td>
<td>0.0331</td>
</tr>
<tr>
<td>DLVARX</td>
<td>0.034</td>
<td>0.0433</td>
<td>0.0278</td>
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<tr>
<td>ARIMA(3, 1, 2)</td>
<td>0.967</td>
<td>0.0231</td>
<td>0.0212</td>
</tr>
<tr>
<td>JP visitors</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HTM</td>
<td>1.000</td>
<td>1.000</td>
<td>0.0266</td>
</tr>
<tr>
<td>LVARX</td>
<td>0.000</td>
<td>0.0551</td>
<td>0.0395</td>
</tr>
<tr>
<td>DLVARX</td>
<td>0.000</td>
<td>0.1356</td>
<td>0.0454</td>
</tr>
<tr>
<td>ARIMA(0, 1, 1)</td>
<td>0.000</td>
<td>0.1140</td>
<td>0.0568</td>
</tr>
<tr>
<td>Room price</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HTM</td>
<td>0.455</td>
<td>0.038</td>
<td>0.0032</td>
</tr>
<tr>
<td>LVARX</td>
<td>0.545</td>
<td>0.0031</td>
<td>0.0108</td>
</tr>
<tr>
<td>DLVARX</td>
<td>0.962</td>
<td>0.00122</td>
<td>0.0050</td>
</tr>
<tr>
<td>ARIMA(0, 1, 0)</td>
<td>0.000</td>
<td>0.0188</td>
<td>0.0272</td>
</tr>
<tr>
<td>Occupancy</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HTM</td>
<td>1.000</td>
<td>1.000</td>
<td>0.0022</td>
</tr>
<tr>
<td>LVARX</td>
<td>0.000</td>
<td>0.0085</td>
<td>0.1160</td>
</tr>
<tr>
<td>DLVARX</td>
<td>0.000</td>
<td>0.0111</td>
<td>0.1218</td>
</tr>
<tr>
<td>ARIMA(2, 1, 3)</td>
<td>1.000</td>
<td>0.0009</td>
<td>0.0357</td>
</tr>
</tbody>
</table>

Note: Each panel presents results for a different target variable. In each case, column 1 lists competitor model \( j \); and columns 6–7 present the Mean Squared Error (MSE) and Mean Absolute Percentage Error (MAPE) for the model \( j \) forecasts. Columns 2–5 list competitor models \( i \) and present the \( p \)-values 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 2 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. For each forecast target, the minimum MSE and MAPE are underlined, as are \( p \)-values below the conventional 5% significance level.

consistent with the findings of many previous studies, but the common observation bears repeating, that structural models like the HTM provide additional benefits over pure time series models by providing structural insight and by permitting scenario analysis. Hall et al.’s (2002) pragmatic approach to identifying structural relationships in a VECM appears to hold promise for tourism modeling and forecasting, as well as for other settings where there are important sources of endogeneity and where available data samples are limited. The approach can be applied wherever the model’s scope can be restricted to a limited number of cointegrating relationships, for example in analyzing demand (and supply) behavior for an overall visitor market, or distinguishing the behavior of two or perhaps three separate markets, for example domestic and international, within a region and outside of the region, etc. And certainly there are markets like Hawaii where one or two source countries dominate arrivals; an example is Las Vegas, where in 2007 88% of visitors were domestic and only 12% were from foreign countries.

The high data demands of this system approach impose some restrictions on its application. As we have noted above, in order to keep the model size manageable we were forced to limit the scope of our analysis to a few key determinants of tourism flows. In particular, we were not able to include some of the demand shifters that often appear in the empirical tourism literature, such as prices of tourism services in competing destinations and policy measures such as tourism marketing expenditures. Our necessarily simpler modeling of the demand side is a limitation of this analysis.

For similar reasons, the VECM approach may become impractical in cases where the practitioner...
wants to estimate relationships for a relatively large number of separate markets. Even here, one could use a VECM approach to model overall visitor activity, to explicitly allow for endogeneity, and then in a second stage estimate a separate set of equations to allocate activity across the destination or source markets. Regardless of the empirical strategy adopted, our results suggest that it is important to address price endogeneity in some way whenever modeling activity in the tourism industry.

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