DYNAMIC MULTIVARIATE ANALYSIS OF A SMALL OPEN ECONOMY: 
THE CASE OF HAWAI'I

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DYNAMIC MULTIVARIATE ANALYSIS OF A SMALL OPEN ECONOMY: THE CASE OF HAWAI'I

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Ting Zhou
This dissertation is dedicated to my parents, Lei Zhou and Yuping Zhao, who have provided unfailing love and support during the process.
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ABSTRACT

The main objective of the dissertation is to apply recent advances in modern econometric analysis, namely cointegrating Vector Autoregression (VAR) and Bayesian VAR (BVAR) to a small open regional economy like Hawaii. This is accomplished in three related yet independent essays demonstrating how regional modeling and forecasting can benefit from these latest developments.

The first essay concentrates on the cointegrating VAR analysis, applying it to Hawaii's premier industry—tourism. Recent research in the literature on identified cointegrating VARs emphasizes the need to rely on economic theory to impose weak exogeneity assumptions, guide the search for long-run just (over) identifying restrictions and shrink the model to the most parsimonious representation. While cointegration analysis has gradually appeared in the empirical tourism literature, the focus has been exclusively on the demand side with no use of the latest identification techniques. A complete Hawaii tourism model is developed, exploiting Hall, Henry, and Greenslade's (2002) theory-directed sequential reduction methodology. Both demand and supply factors are emphasized in identifying long-run cointegrating relationships.

The second essay applies the BVAR methodology to another key sector in regional modeling—construction. This essay represents the first application of priors on linear combinations of parameters—namely, sums of coefficients and dummy initial observation priors— in a BVAR construction forecasting model. I find that including these priors does not necessarily improve forecast accuracy at medium to long horizons, especially when the series are integrated and there is more than one cointegrating relationship.

The third essay extends the second essay to deal with the entire regional economy. All regional models must deal with the inavailability of expenditure data at the state and local levels. This problem typically leads researchers to use either a single highly restricted VAR, or BVAR, or a model of pseudo theory driven
equations. In contrast, my third essay makes use of BVAR blocks to model proxies for the expenditure categories in a traditional macro structure. Compared with existing regional BVAR models, the current setup is more complete in accounting for both the *intra*-action of sectors within the region and the *inter*-action of the region with external drivers.
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1.1 Introduction

The extraordinary growth in international tourism since World War II has attracted much interest in business, government, and academic circles. At the same time, advances in econometric methods have provided researchers with new tools to study tourism markets. While research has been overwhelmingly based on traditional regression techniques, recent years have witnessed a surge in the application of newly developed time series methods to deal with integrated and potentially cointegrated series.

One of the most important issues in cointegration analysis is identification. Pesaran and Shin (2001) show that when the cointegrating rank is $r$, exact identification requires imposing $r$ restrictions in each of the $r$ cointegrating vectors. In recent years, interest on the identification of structural relationships in cointegrated systems has grown. Pesaran and Smith (1998) and Pesaran and Shin (2001) dismiss the commonly adopted practice of Johansen (1988, 1991, 1995) as a pure mathematical convenience, and have advocated an alternative theory-based

\footnote{For a review, refer to Lim (1997), Crouch (1994a, 1994b), and Witt and Witt (1992, 1995).}
approach to achieve identification. Hall, Henry, and Greenslade (2002) argue that the different identification methods proposed in the literature are almost impossible to implement successfully due to the sample sizes available in typical economic problems. They suggest imposing theory-based weak exogeneity assumptions at the earliest stage of the model reduction process.

In light of these advances, existing cointegration analysis of tourism models may suffer from three deficiencies. First, very few cointegrating models considered the supply of tourism. This is rather unfortunate as short-run price fluctuations and long-term stock adjustments are clearly one side of the theoretical model to determine market equilibrium. Furthermore, these adjustments are potentially important aspects of empirical tourism modeling, and neglecting the supply side may lead to biased estimates of demand elasticities. Second, recent empirical tourism research significantly lags behind latest developments in time series econometrics. Some researchers still rely on the Engle-Granger two-step approach developed in the late 1980s with little or no mention of potential endogeneity problems. While researchers have recently begun to adopt the system approach, identification is invariably achieved by the Johansen's reduced rank regression technique, despite the fact that alternative theory-based identification methods are available. Third, existing cointegrating VARs are invariably closed form, although it is hard to imagine how economic activity in a local tourism market can exert significant impacts on the economy of a major tourism originating country. As a result, such systems are potentially subject to the identification problem discussed in Hall, Henry, and Greenslade (2002).

This paper aims to construct a reasonably complete tourism model for Hawaii adopting the latest cointegrating analysis techniques. It makes a contribution to the existing literature in three aspects. First, the supply decision is formally incorporated to guide the search for economically meaningful long-run cointegrating vectors. Second, rather than rely on the "mathematically

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convenient” identification method of Johansen, I follow Pesaran and Smith (1998) and Pesaran and Shin (2001) theory-based approach in identifying long-run cointegrating vectors. Third, theory based exogeneity assumptions are tested and imposed at the earliest stage of the model reduction process. The purpose of each of these modeling strategies is to increase the likelihood of identifying the “true” equilibrium relationships that govern tourism activity in Hawaii.

The organization of the paper is as follows. Section 1.2 derives the tourism demand and supply equations, and identifies the variables to be used in the modeling exercise. Section 1.3 outlines estimation methodologies, such as cointegration, identification, weak exogeneity, and sequential system reduction. Section 1.4 presents the empirical results of the Hawaii tourism model. Section 1.5 evaluates the forecast performance of the model. Section 1.6 concludes.

1.2 The Demand and Supply of Tourism

Designing an appropriate tourism model requires conceptualizing the economics of tourism activities. However, theoretical studies are rare. Some early perspectives are reflected in Quandt (1970) and Gray (1970). More recently, Bull (1991) and Sinclair and Stabler (1997) attempt to give textbook overviews of tourism theory. A few optimizing models have been developed (Copeland, 1989, 1990; Morely, 1992; and Taylor, 1995). While theoretical work is relatively sparse, the empirical literature on tourism is substantial.

1.2.1 Tourism Demand

Due to the lack of tourism-specific theory, almost all empirical models borrow heavily from basic consumer theory (Varian, 1992) where a Marshallian demand for the tourism product is expressed as,

\[ D_{ij} = F(Y_i, P_i, P_j, P_j^S, Z), \] (1.1)
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 $Z$ is a vector of other factors affecting tourism demand. When homogeneity is assumed, demand can be expressed as a function of income in constant domestic prices and destination and substitute prices in relative terms,

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

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 perceived 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 (1994a), 63% choose the number of visitor arrivals as the measure of demand while 48% use expenditure and receipts.

Consumer theory prescribes that the optimal consumption bundle depends on the consumer's income, the price of the good, the prices of related goods (substitutes and/or complements), and other demand shifters. While it is common to accept income as the major demand determinant, the specific form varies greatly from study to study. Typical income measures include the gross domestic product (GDP), gross national product (GNP), national disposable income (NDI), personal income (PI) and consumption expenditure (CE), measured in either real, nominal, aggregate, or per capita form, depending on data availability and nature of tourism demand modelled. Generally speaking, PI and CE are used to model leisure and holiday travels, while GDP, GNP, and NDI are used to model business travels. As
for the choice between nominal and real incomes, equations (1.1) and (1.2) make it clear that both are acceptable, provided that prices are specified appropriately. The 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. Nevertheless, the inclusion of population as a separate variable distinct from aggregate income is itself questionable (Gangnes and Bonham, 1998).

Two types of price appear in the demand specification. The first is the own price of tourism products, normally approximated by the consumer price index (CPI) in the destination country. The practice is sometimes criticized on the ground 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). So occasionally tourism-specific prices or indices are employed. Martin and Witt (1987) report that tourism-specific indices do not perform any better than overall indices such as the CPI. Edwards (1995) prefers the CPI because the coverage of tourism-specific price indices are suspect (Witt and Witt, 1992).

The second price used in demand equations is the substitute price. On one hand, domestic travel is often found to be the strongest substitute for foreign travel, justifying the inclusion of a price index for other domestic goods and services, such as the CPI in the county of origin. On the other hand, competition among different overseas destinations may call for the inclusion of variables that represent the cost of substitute destinations. In the existing literature, most models employ an exchange rate adjusted relative CPI (or real exchange rate) to capture the substitution between domestic vacations and overseas holiday travel. To capture substitution among different overseas destinations, a number of studies include real exchange rate from a number of competing countries, while others use a weighted real exchange rates to capture the general effect (for examples of the former, see Kim and Song, 1998 and Song, Romilly and Liu, 2000; for the latter, see Vogt and Wittayakorn, 1998).

---

4For instance, Gangnes and Bonham (1998) use the hotel room price.
Transportation cost is another potentially important factor in determining international travel. Song and Witt (2000) suggest using “representative air fares between origin and destination for air travel” to approximate the true travel cost, but Gangnes and Bonham (1998) reject such practice on the ground that “frequent discounting and package trips” implies a significantly lower actual price than published fares. They recommend Edwards (1995) measure of International Air Transport Association (IATA) data on revenues per passenger ton/km. From a statistical perspective, the transportation cost variable may enter either separately or merges with living cost to form a comprehensive cost measurement. The latter has the advantage of preserving degrees of freedom, however, the estimated parameter is harder to interpret.

The exchange rate is logically among the most influential factors in determining international travel. This effect is usually captured by converting destination prices into the currency of the tourism importing country. However, Lathiras and Siriopoulos (1998) and Vogt and Wittayakorn (1998) insist that exchange rates, either as a single bilateral rate or a composite index, must be considered separately because tourists respond very differently to changes in price levels and exchange rate fluctuations (which, some argue, is more obvious than destination cost-of-living fluctuations). Research finds that the exchange rate adjusted CPI, either alone or together with a separate exchange rate variable, is a good proxy for tourism cost, while the exchange rate itself is not (Martin and Witt, 1987).

Apart from the variables listed above, many studies also use a time trend (linear or nonlinear as in Witt and Witt, 1992) to capture consumer tastes; a constant term to account for “utility image” that do not vary greatly with time; and dummies to account for various once-off events such as the Olympic Games, large-scale fairs, foreign currency/travel restrictions and oil crises. These types of events, if otherwise neglected, might lead to bias in the estimated parameters (Anastasopoulos, 1984; Crouch, Schultz and Valerio, 1992; Kliman, 1981; Mak, Moncur and Yonamine, 1977). In other cases, dummy variables are used to account

---

5See Fujii and Mak (1985) and Crouch (1991) for examples.
for switches in data sources, inconsistency in recording methods, and seasonality.

For the Hawaii tourism model under consideration, I choose the number of visitor arrivals as the dependent variable due to the unavailability of high frequency expenditure data. One possibility is to model total visitor arrivals, and the corresponding income and price measurements will be a world income proxy and a world price index. While theoretically feasible, the approach is empirically unappealing as it does not capture any specific market of interest. Instead, I attempt to identify one demand relationship each for the U.S. and Japanese visitors, as tourists from the two markets have consistently accounted for over 85% of all visitors to Hawaii during the last decade.

To keep the model size under control, I choose to model the main determinants of tourism demand while leaving out ones that are less important or simply difficult to approximate. The model is therefore down to five demand determinants. They are U.S. real personal income ($nir_{us}$), the U.S. consumer price index ($cpi_{us}$), Japanese real personal income ($nir_{jp}$), the Japanese exchange rate adjusted CPI ($p_{jp}$) and the Hawaii average daily hotel room price ($prm_{hi}$). In linear form, the demand relations are:

\[
\begin{align*}
    vus_{hi} &= \alpha_0 + \alpha_1 * nir_{us} + \alpha_2 * cpi_{us} + \alpha_3 * prm_{hi} + e_{us}, \quad (1.3) \\
    vjp_{hi} &= \beta_0 + \beta_1 * nir_{jp} + \beta_2 * p_{jp} + \beta_3 * prm_{hi} + e_{jp}. \quad (1.4)
\end{align*}
\]

The definition of variables is listed in table 1.1. All series are of quarterly frequency and in logarithm. $e_{us}$ and $e_{jp}$ are regression residuals and capture any unexplained demand. Details on the construction of U.S. and Japanese arrival series are in Appendix.

### 1.2.2 Tourism Supply

Both theoretical and empirical research on the supply of tourism services is scarce (Crouch, 1994a). In the limited literature, supply is typically assumed to
Table 1.1: 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_hi</td>
<td>U.S. visitors to Hawaii</td>
<td>000s</td>
<td>Calculated</td>
</tr>
<tr>
<td>vjp_hi</td>
<td>Japanese visitors to Hawaii</td>
<td>000s</td>
<td>Calculated</td>
</tr>
<tr>
<td>prm_hi</td>
<td>Hawaii average daily hotel room rate</td>
<td>dollar</td>
<td>DBEDT</td>
</tr>
<tr>
<td>ocup_hi</td>
<td>Hawaii average daily hotel occupancy rate</td>
<td>%</td>
<td>DBEDT</td>
</tr>
<tr>
<td>trms_hi</td>
<td>Hawaii visitor plant inventory</td>
<td>000s</td>
<td>DBEDT</td>
</tr>
<tr>
<td><strong>U.S. Variables</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>nir_us</td>
<td>U.S. real personal income</td>
<td>bil 82-84$</td>
<td>BEA</td>
</tr>
<tr>
<td>cpi_us</td>
<td>U.S. 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>nir_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>yxr_jp</td>
<td>yen/dollar exchange rate</td>
<td>yen/dollar</td>
<td>FED</td>
</tr>
<tr>
<td><strong>Calculated Variables</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>p_jp</td>
<td>cpi_jp/yxr_jp</td>
<td>–</td>
<td>Calculated</td>
</tr>
</tbody>
</table>

BEA: Bureau of Economic Analysis, U.S.
FED: Federal Reserve Bank at St. Louis.
ESRI: Economic and Social Research Institute, Japan.
SBSC: Statistics Bureau and Statistics Center, Japan.
be infinitely elastic, and parameters—of assumed demand relations—are estimated by Ordinary Least Squares (OLS). However, the infinite elasticity assumption is a convenient simplification rather than a tested hypothesis. Fujii, Khaled, and Mak (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 as hoteliers try to operate near-full capacity. It is well known in the econometric literature that when the supply elasticity is less than infinity, OLS estimates of a price and quantity relation may be a demand relation, a supply relation or a hybrid of the two depending on individual error variances of each curve (see for example, Maddala 1992). The treatment of supply relations is therefore indispensable in deriving true demand (and possibly supply) elasticities.

However, given the variety of products tourists consume, it is rather difficult to give a precise definition of tourism supply. Because lodging service is the largest single product category in overall tourists expenditures in Hawaii,\(^6\) I treat hotel accommodations as my proxy for the supply of tourism services. Hotel products are nonstorable. A hotel room not rented for a given day is lost forever as a potential source of revenue. This, together with heavy operating costs, creates a strong incentive for profit maximizing hotel owners to maintain high occupancy rates. In the short run, for a given supply of hotel rooms, hotel operators rely on price discriminations and off-peak discounts to maintain high occupancy. Over longer horizons, capacities are adjusted through expansion and contraction of inventory.

In the limited literature on hotel supply, some seek to estimate an inverted tourism supply curve, most commonly found in hotel room tax literature (Fujii, Khaled and Mak, 1985; Bonham and Gangnes, 1996). The supply price of hotel rooms is assumed to be a mark-up over marginal cost,

\[
P_H = \text{markup} \cdot MC = M \cdot H(Q_H, P_L, P_K, P_Z, K_H);\tag{1.5}
\]

where \(Q_H\) is the total quantity supplied, i.e., the number of rooms rented; \(P_L, P_K\)

\(^6\)Over the past three decades, visitors to Hawaii have spent an average of 33\% of total expenditures on hotel lodging services.
and $P_Z$ are the input prices of labor, capital and other inputs; $M$ is the markup factor; and $K_H$ is the short-run given hotel room supply. Assuming that marginal cost is homogeneous of degree one in input prices, equation (1.5) is equivalently written as,

$$\frac{P_H}{P_K} = M \cdot H(Q_H, \frac{P_L}{P_K}, \frac{P_Z}{P_K}, K_H).$$  \hspace{1cm} (1.6)

In the paper, I model the hotel room rate as,

$$prm_{hi} = L(Q^{Rented}, P^{Cost}, trms_{hi}),$$  \hspace{1cm} (1.7)

where $Q^{Rented}$ is the total rooms rented and $P^{Cost}$ measures the overall production cost. Since an exact number of hotel rooms occupied is not available, proxies are found in visitor arrivals to the islands (the sum of U.S. and Japanese tourists) and the hotel occupancy rate. As for production cost, it would be ideal to include Hawaii specific operation cost measurements—Hawaii producer price index for example. But such an index does not exist. Considering the model size (9 variables) and limited data set (86 observations), I decide not to include another proxy variable. U.S. consumer price index ($cpi_{us}$) may partially capture the cost effect. In linear form, the supply relation becomes,

$$prm_{hi} = \gamma_0 + \gamma_1 \ast (vus_{hi} + vjp_{hi}) + \gamma_2 \ast ocup_{hi}$$
$$+ \gamma_3 \ast cpi_{us} + \gamma_4 \ast trms_{hi} + e_{prm}. \hspace{1cm} (1.8)$$

1.3 The Methodology

The Hawaii tourism model is chosen following recent methods in cointegration analysis, namely theory-guided identification. There are several building blocks to the methodology, starting with the Johansen's reduced rank regression technique. This section reviews related topics and is organized as follows: Section 1.3.1 outlines Johansen's (1988) procedure. Section 1.3.2 presents various proposals to achieve long-run identification. Section 1.3.3 discusses weak exogeneity and
extends the basic Johansen procedure to cover weakly exogenous I(1) variables. Section 1.3.4 deals with deterministic variables in cointegrated systems. Section 1.3.5 illustrates the sequential model reduction strategy advocated by Hall, Henry, and Greenslade (2002).

1.3.1 Johansen Reduced Rank Regression Technique

Consider a VAR(k) model in an $m \times 1$ vector of I(1) variables, $z_t$,

$$ z_t = \Phi_1 z_{t-1} + \cdots + \Phi_k z_{t-k} + c + \epsilon_t, \quad t = 1, 2, \ldots, T, \tag{1.9} $$

where $k$, the order of the VAR, is assumed to be known a priori; $c$ is an $m \times 1$ vector of unknown deterministic terms; $\Phi_i, i = 1, 2, \ldots, k$, are $m \times m$ matrices of unknown parameters; $\epsilon_t$ is an $m \times 1$ vector of disturbances that is i.i.d. $(0, \Omega)$ and the initial values, $z_0, z_{-1}, \ldots, z_{-k+1}$ are given. It is also assumed that the roots of

$$ | I_n - \Phi_1 \lambda - \Phi_2 \lambda^2 - \cdots - \Phi_k \lambda^k | = 0 \tag{1.10} $$

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).\(^7\)

The model specified in (1.9) can be reparameterized as the Vector Error Correction Model (VECM),

$$ \Delta z_t = -\Pi z_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta z_{t-i} + c + \epsilon_t, \quad t = 1, 2, \ldots, T, \tag{1.11} $$

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 property of (1.11) is characterized by the rank of $\Pi$. If all elements of $z_t$ are stationary, $\Pi$ is a full rank $m \times m$ matrix. If the elements of $z_t$ are I(1) but not cointegrated, $\Pi$ is of rank zero, and a VAR model in first differences is appropriate. If the elements of $z_t$ are I(1) and cointegrated with $\text{rank}(\Pi) = r$, $\Pi$ can be decomposed into two $m \times r$ full column rank matrices $\alpha$ and $\beta$ where $\Pi = \alpha \beta'$.

\(^7\)A review of the econometric analysis of I(2) variables is provided in Haldrup (1998).
This implies that there are $r < m$ linear combinations of $z_t$, $\xi_t = \beta' z_t$, that are stationary. The matrix of adjustment coefficients, $\alpha$, measures how strongly deviations from the long-run equilibrium, $\xi_t$, feedback onto the system. The identification problem arises because $\alpha$ and $\beta$ are not uniquely identified without additional information. To see this, note that for any $r \times r$ non-singular matrix $\mathbf{Q}$ we can define matrices $\alpha^* = \alpha \mathbf{Q}$ and $\beta^* = \mathbf{Q}^{-1} \beta'$ such that $\Pi = \alpha^* \beta^* = \alpha \mathbf{Q} \mathbf{Q}^{-1} \beta' = \alpha \beta'$.

The Johansen reduced rank regression technique involves maximizing the log likelihood function of equation (1.11), subject to the constraint that $\Pi$ can be decomposed into two $m \times r$ full column rank matrices $\alpha$ and $\beta$ such that $\Pi = \alpha \beta'$. For a sample of $T + k$ observations on $z_t$, $(z_{-k+1}, z_{-k+2}, \ldots, z_T)$, when the disturbances $\epsilon_t$ are Gaussian, the log likelihood of $(z_1, z_2, \ldots, z_T)$ conditional on $(z_{-k+1}, z_{-k+2}, \ldots, z_0)$ is given by,

$$L(\Omega; \Gamma_1, \Gamma_2, \ldots, \Gamma_{k-1}, c, \Pi) = (-T m/2) log(2\pi) - (T/2) log |\Omega| -$$

$$(1/2) \sum_{t=1}^{T} \left[ (\Delta z_t - \Gamma_1 \Delta z_{t-1} - \cdots - \Gamma_{k-1} \Delta z_{t-k+1} - c - \Pi z_{t-1})' \times \Omega^{-1} \times (\Delta z_t - \Gamma_1 \Delta z_{t-1} - \cdots - \Gamma_{k-1} \Delta z_{t-k+1} - c - \Pi z_{t-1}) \right].$$

(1.12)

To solve this maximization problem, Johansen first concentrates the constant and dynamic parameters $(c, \Gamma_1, \Gamma_2, \ldots, \Gamma_{k-1})$ out of the likelihood function by individually regressing $\Delta z_t$ and $z_{t-1}$ on a constant and $\Delta z_{t-1}, \Delta z_{t-2}, \ldots, \Delta z_{t-k+1}$ using OLS. Specifically, he estimates the following equations,

$$\Delta z_t = \hat{\Psi} + \hat{\Psi}_1 \Delta z_{t-1} + \hat{\Psi}_2 \Delta z_{t-2} + \cdots + \hat{\Psi}_{k-1} \Delta z_{t-k+1} + \hat{u}_t,$$

(1.13)

$$z_{t-1} = \hat{\Theta} + \hat{\Theta}_1 \Delta z_{t-1} + \hat{\Theta}_2 \Delta z_{t-2} + \cdots + \hat{\Theta}_{k-1} \Delta z_{t-k+1} + \hat{v}_t,$$

(1.14)
and uses the regression residuals, $\widehat{u}_t$ and $\widehat{v}_t$, to simplify the likelihood function as

$$G(\Omega, \Pi) \equiv L\{\Omega, \widehat{\Gamma}_1^*(\Pi), \widehat{\Gamma}_2^*(\Pi), \ldots, \widehat{\Gamma}_{k-1}^*(\Pi), \widehat{\Sigma}^*(\Pi), \Pi\}$$

$$= - (Tm/2) \log(2\pi) - (T/2) \log | \Omega |$$

$$- (1/2) \sum_{t=1}^{T} [ (\widehat{u}_t - \Pi \widehat{v}_t)' \Omega^{-1} (\widehat{u}_t - \Pi \widehat{v}_t) ].$$

(1.15)

To concentrate the likelihood function one step further, the $\Omega$ matrix is replaced by

$$\widehat{\Omega}^*(\Pi) = (1/T) \sum_{t=1}^{T} [ (\widehat{u}_t - \Pi \widehat{v}_t)(\widehat{u}_t - \Pi \widehat{v}_t)' ]$$

(1.16)

and the likelihood function becomes

$$H(\Pi) \equiv G(\widehat{\Omega}^*(\Pi), \Pi)$$

$$= - (Tm/2) \log(2\pi) - (T/2) \log | \widehat{\Omega}^*(\Pi) | - (Tm/2)$$

$$- (T/2) \log | (1/T) \sum_{t=1}^{T} [ (\widehat{u}_t - \Pi \widehat{v}_t)(\widehat{u}_t - \Pi \widehat{v}_t)' ] | .$$

(1.17)

Maximizing the likelihood function boils down to choosing $\Pi$ to minimize

$$(1/T) \sum_{t=1}^{T} [ (\widehat{u}_t - \Pi \widehat{v}_t)(\widehat{u}_t - \Pi \widehat{v}_t)' ]$$

subject to the constraint that $\text{rank}(\Pi) = r$. Under the constraint, the optimization problem is equivalent to finding the $r$ largest canonical correlations between $\widehat{u}_t$ and $\widehat{v}_t$. This is accomplished by selecting the largest $r$ elements of normalized eigenvectors of the matrix $\widehat{\Sigma}_{UV}^{-1} \widehat{\Sigma}_{UU} \widehat{\Sigma}_{UU}^{-1} \widehat{\Sigma}_{UV}$ where $\widehat{\Sigma}_{VV}, \widehat{\Sigma}_{VU}, \widehat{\Sigma}_{UU}$ and $\widehat{\Sigma}_{UV}$ are the sample moment matrices defined as

$$\widehat{\Sigma}_{UU} = (1/T) \sum_{t=1}^{T} \widehat{u}_t \widehat{u}_t',$$

$$\widehat{\Sigma}_{VV} = (1/T) \sum_{t=1}^{T} \widehat{v}_t \widehat{v}_t',$$

$$\widehat{\Sigma}_{UV} = (1/T) \sum_{t=1}^{T} \widehat{u}_t \widehat{v}_t,'$$

(1.18)

The intuition behind the Johansen procedure is easily seen when we acknowledge the two driving forces of $\Delta z_t$ (see equation (1.11)). First, $\Delta z_t$ may be serially correlated, reflecting the structural, technological or gestational lags
typical for many economic variables. Second, for an economic system to be stable, any deviations from equilibrium need to be corrected and $\Delta z_t$ contains an “error correction” mechanism. The first step in the Johansen procedure of regressing $\Delta z_t$ and $z_{t-1}$ on a constant and $\Delta z_{t-1}, \Delta z_{t-2}, \ldots, \Delta z_{t-k+1}$ removes the direct impact of short-run dynamics on $\Delta z_t$ and any impact of $z_{t-1}$ on $\Delta z_t$ through its correlation with short-run dynamics, thus ensuring that the canonical correlations between the residuals capture movements in $\Delta z_t$ that are solely due to the error correction effect.

### 1.3.2 Identification

From section (1.3.1), the decomposition of the $\Pi$ matrix in equation (1.11) into two $m \times r$ matrices $\alpha$ and $\beta$ is not unique. There exist multiple $\beta$'s that give the same value for the maximized log-likelihood function and identification is called for. Pesaran and Shin (2001) show that a total of $r^2$ restrictions are needed for exact identification where $r = \text{rank} (\Pi)$ is the cointegration rank. In addition, the $r^2$ restrictions must be evenly distributed across the cointegrating vectors so there are $r$ restrictions per vector.

The literature contains various methods to impose the necessary $r^2$ restrictions. Johansen’s statistical approach is the most widely used. It is considered a pure “empirical” or “statistical” approach because identification restrictions involve only the observation matrices $(\Sigma_{VV} - \Sigma_{VU} \Sigma_{UU}^{-1} \Sigma_{UV})$ and $\Sigma_{VV}$ derived from the sample moment matrices in (1.18). Specifically, Johansen’s just identified estimator of $\beta$ (denoted $\hat{\beta}_J$) is the $r$ largest eigenvalues of $\hat{\Sigma}_{VV}^{-1} \hat{\Sigma}_{VU} \hat{\Sigma}_{UU}^{-1} \hat{\Sigma}_{UV}$ subject to the following “ortho-normalization” and “orthogonalization” restrictions,

$$\hat{\beta}_J \hat{\Sigma}_{VV} \hat{\beta}_J = I_r,$$
$$\hat{\beta}_{ji} \hat{\Sigma}_{VU} \hat{\Sigma}_{UU}^{-1} \hat{\Sigma}_{UV} \hat{\beta}_{jj} = 0, \quad i \neq j, \quad i, j = 1, 2, \ldots, r. \quad (1.19)$$

where $\hat{\beta}_{ji}$ is the $i$-th column of $\hat{\beta}_J$. The first condition above supplies $r(r+1)/2$ restrictions and the second supplies an additional $r(r-1)/2$ restrictions. Together
exactly $r^2$ just-identifying restrictions are imposed. In the recent literature, Johansen’s statistical approach has been criticized as a “pure mathematical convenience” (Pesaran and Shin, 2001), rather than a theoretically justified approach. Nonetheless, it is widely available in econometric softwares because it generates the basic cointegrating vectors on which theory-based restrictions can be tested and imposed.

Besides Johansen’s reduced rank approach, another popular identification method found in the literature is Phillips’ triangularization approach. Phillips (1991, 1995) shows that if an $(m \times 1)$ vector $z_t$ is characterized by exactly $r$ cointegrating relations, it is always possible to decompose $z_t$ into a $r \times 1$ vector $z_{1t}$, and an $(m - r) \times 1$ vector $z_{2t}$, such that $z_{2t}$ are not cointegrated among themselves. To follow this decomposition approach, however, the number of cointegrating relations $(r)$ must be known a priori. In the context of the VECM, the decomposition implies the following restrictions on the $\Pi$ matrix

$$
\Pi = \begin{pmatrix} 
\Pi_{11} & \Pi_{12} \\
0 & 0 
\end{pmatrix} = \alpha \beta',
$$

(1.21)

where $\Pi_{11}$ is a non-singular matrix and

$$
\alpha = \begin{pmatrix} \Pi_{11} \\
0 
\end{pmatrix}, \quad \beta = \begin{pmatrix} I_r & \Pi_{11}^{-1} \Pi_{12} \end{pmatrix}.
$$

(1.22)

It is clear that Phillips’ approach achieves exact identification by placing $r^2$ restrictions on the first $r$ rows of $\beta$ such that the coefficients of $z_{1t}$ in the long-run relations, $\beta' z_{t-1}$, equal an identity matrix. Note also that the approach imposes $(m - r) \times r$ additional zero restrictions on the loading coefficient matrix $\alpha$. These restrictions are not required for long-run identification, but arise from the subsidiary assumption that $z_{2t}$ are not cointegrated among themselves.

Phillips’ approach differs from Johansen’s procedure in three respects. First, the two approaches adopt different methodologies in determining the cointegrating rank. In Phillips’ framework, $r$ is known a priori and therefore does not depend
on sample observations. As such, the approach does not require a fully-specified dynamic model. Johansen's approach, however, works only in a model with fully-specified dynamics. It is purely statistical and hinges closely on the sample observations under study. Therefore, it is possible for Johansen's approach to find a varying number of cointegrating vectors for different sample periods. Second, the number of identifying restrictions imposed by the two approaches differs. Johansen's approach imposes $r^2$ restrictions to achieve exact identification. Phillips' approach, on the other hand, not only imposes $r^2$ exact identifying restrictions on the first $r$ rows of the $\beta$ matrix but also imposes a second set of restrictions on the $\alpha$ matrix that are not required for identification and may not hold in practice. Third, the $z_{2t}$ vector under Phillips' triangular characterization is weakly exogenous (a concept to be introduced in the next section). It is clear from equation (1.22) that under Phillips' framework, each endogenous variable can only cointegrate with the set of weakly exogenous variables, however not other endogenous variables. In contrast, Johansen's approach accounts for cointegrating relations among all variables, both endogenous and weakly exogenous.

The latest developments in cointegration analysis emphasize the use of economic theory in guiding the search for long-run exact/over identifying restrictions (Pesaran and Shin, 2001). 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. Typically the approach imposes exclusion and normalization restrictions to exactly identify the system and then uses $\chi^2$ statistics to test over identifying restrictions. To illustrate, the Hawaii tourism model has nine variables $z_t = (vus.hi, vjp.hi, prm.hi, ocup.hi, trms.hi, nir.us, cpi.us, nir.jp, p.jp)$ (see table 1.1 for variable definitions). Tourism demand and supply theories suggest the existence of three long-run cointegrating
vectors,

\[ vus\_hi = \alpha_0 + \alpha_1 * nir\_us + \alpha_2 * cpi\_us + \alpha_3 * \text{prm\_hi} + e_{us}, \]

\[ vjp\_hi = \beta_0 + \beta_1 * nir\_jp + \beta_2 * p\_jp + \beta_3 * \text{prm\_hi} + e_{jp}, \]

\[ \text{prm\_hi} = \gamma_0 + \gamma_1 * (vus\_hi + vjp\_hi) + \gamma_2 * ocup\_hi \]
\[ + \gamma_3 * cpi\_us + \gamma_4 * trms\_hi + e_{\text{prm}.} \]

(1.23) (1.24) (1.25)

One set of exact identifying restrictions may: 1) exclude \(vjp\_hi, nir\_jp\) from the U.S. demand relation and normalize on \(vus\_hi\); 2) exclude \(vus\_hi, nir\_us\) from the Japan demand relation and normalize on \(vjp\_hi\); and 3) exclude \(nir\_us, nir\_jp\) from the Hawaii supply relation and normalize on \(\text{prm\_hi}\). Starting from the exactly identified system, over identifying restrictions are tested either individually or in a group. Details on the tests performed are found in section 1.4.

1.3.3 Johansen Procedure with Weakly Exogenous I(1) Variables

The VAR system in (1.9) has traditionally suffered from the over-parameterization problem: each equation of the VAR involves estimating \(m \times k\) 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, if all nine variables are treated as endogenous with a lag of four, each equation in the Hawaii tourism model in section 1.2 involves estimating 38 parameters and the system as a whole has 342 regression coefficients. With a sample size of 86 (1980Q1–2001Q2), the VAR approach quickly runs into the problem of severe lack of degrees of freedom. In-sample regressions produce perfect fit, 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 \((m \times k + d), d\) being the number of deterministic components. For the Hawaii
tourism model, if the external drivers \((nir\_us, nir\_jp, cpi\_us, p\_jp)\) are treated as weakly exogenous, the number of equations is reduced from nine to five and parameters to be estimated from 342 to 190.

**Weak Exogeneity and Partial Systems**

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 \(q = m - n\). The primary interest is 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 the error terms in the VECM equation (1.11) can be partitioned conformably as \(c = (c'_y, c'_x)', \alpha = (\alpha'_y, \alpha'_x)', \Gamma_i = (\Gamma'_y, \Gamma'_x)', i = 1, 2, \ldots, k - 1, \epsilon_t = (\epsilon'_y, \epsilon'_x)'\) and the variance-covariance matrix as

\[
\Omega = \begin{pmatrix} \Omega_{yy} & \Omega_{yz} \\ \Omega_{xy} & \Omega_{xx} \end{pmatrix}.
\]

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

\[
\Delta y_t = c_y - \omega c_x + \omega \Delta x_t + (\alpha_y - \omega \alpha_x)\beta'z_{t-1} + \sum_{i=1}^{k-1} (\Gamma'_y - \omega \Gamma'_x)\Delta z_{t-i} + \epsilon_y - \omega \epsilon_x,
\]

and a marginal model for \(x_t\),

\[
\Delta x_t = c_x + \alpha_x \beta'z_{t-1} + \sum_{i=1}^{k-1} \Gamma_x \Delta z_{t-i} + \epsilon_x,
\]

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

For the system in equation (1.26) and (1.27), the cointegrating relations \(\beta'z_{t-1}\) enter both the conditional and the marginal model, and the new adjustment coefficients \((\alpha_y - \omega \alpha_x)\) depend on the error variance-covariance matrix \((\Omega)\) and all the adjustment coefficients \((\alpha_y, \alpha_x)\). In general parameters in the marginal and the conditional system are interrelated and a full system analysis is required for estimation.
There exists, however, a special case in which the conditional model (1.26) contains as much information about the cointegrating relations, $\beta'z_{t-1}$, as the full system and the analysis of the conditional model is efficient. This is the case when $x_t$ is weakly exogenous. Two conditions must be satisfied for $x_t$ to be weakly exogenous:

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.

Specifically, if the parameters of interest are the cointegrating vector $\beta$, $x_t$ is weakly exogenous if and only if $\alpha_x = 0$ (Johansen, 1990). This condition ensures that $\beta$ does not appear in the marginal distribution for $x_t$ (see equation (1.27)), and that $\alpha_x$ does not appear in the conditional model (see equation (1.26)).

The weak exogeneity assumption hinges closely on the parameters of interest. The condition $\alpha_x = 0$ is a necessary and sufficient condition for weak exogeneity of $x_t$ only when the parameter of interest is $\beta$. This often proves to be too strong a condition for inference because exogenous variables may form cointegrating relationships among themselves (Pesaran, Shin, and Smith, 2000). Harbo, Johansen, Nielsen, and Rahbek (1998) propose an alternative weak exogeneity test. 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 relations to the marginal model. Their approach avoids the common failure of weak exogeneity due to the cointegration among weakly exogenous variables.

**Johansen Procedure With Weakly Exogenous I(1) Variables**

From section 1.3.1, the Johansen procedure involves finding the $r$ largest canonical correlations between $\Delta z_t$ and $z_{t-1}$ after the short-run effects, $\Delta z_{t-1}$, $\Delta z_{t-2}, \ldots, \Delta z_{t-k+1}$, are removed. It is straightforward to extend the technique to
the case of weakly exogenous I(1) variables. This extension involves the following steps:

1. Individually regress $\Delta y_t$ and $z_{t-1}$ on a constant and $\Delta x_t$, $\Delta z_{t-1}$, $\Delta z_{t-2}$, ..., $\Delta z_{t-k+1}$ using OLS. Collect the regression residuals in two vectors $\hat{u}_t$ ($n \times 1$) and $\hat{v}_t$ ($m \times 1$).

2. Calculate the sample moment matrices,

$$\hat{\Sigma}_{UU} = (1/T) \sum_{t=1}^{T} \hat{u}_t \hat{u}_t'$$
$$\hat{\Sigma}_{VV} = (1/T) \sum_{t=1}^{T} \hat{v}_t \hat{v}_t'$$
$$\hat{\Sigma}_{UV} = \hat{\Sigma}_{VU}' = (1/T) \sum_{t=1}^{T} \hat{u}_t \hat{v}_t'$$

with dimensions $\hat{\Sigma}_{UU}$ ($n \times n$), $\hat{\Sigma}_{VV}$ ($m \times m$), $\hat{\Sigma}_{UV}$ ($n \times m$) and $\hat{\Sigma}_{VU}$ ($m \times n$).

3. Find the $r$ $m \times 1$ eigenvectors $(\hat{\eta}_i, i = 1, 2, \ldots, r)$ corresponding to the $r$ largest eigenvalues $\hat{\lambda}_1 > \hat{\lambda}_2 > \ldots > 0$ of the $m \times m$ matrix $\hat{\Sigma}_{VV}^{-1} \hat{\Sigma}_{UV} \hat{\Sigma}_{VU}^{-1} \hat{\Sigma}_{UV}$ with normalization $\hat{\eta}_i' \hat{\Sigma}_{VV} \hat{\eta}_i = 1$. These eigenvalues constitute the columns of the $\hat{\beta}$ matrix and the basis for the cointegrating space, i.e., any cointegrating vector can be written in the form $v = b_1 \hat{\eta}_1 + b_2 \hat{\eta}_2 + \cdots + b_r \hat{\eta}_r$. The loading matrix $\alpha_y$ is given by $\hat{\alpha}_y = -\hat{\Sigma}_{UV} \hat{\beta}$.

Note that the identification procedures outlined in Section 1.3.2 applies perfectly here.

1.3.4 Deterministic Variables in VECM

A closely related question to identification is the specification for deterministic variables. Our discussion so far has focused on a VECM with a time trend restricted to the cointegration space and an unrestricted intercept. In the literature, there are at least four other cases. All five cases and the corresponding Johansen procedure are summarized below (see Pesaran, Shin and Smith, 2000).
Case I: (No Intercepts; No Trends.) The structural VECM is

\[ \Delta y_t = \Pi_y z_{t-1} + \omega \Delta x_t + \sum_{i=1}^{k-1} \Gamma_i \Delta z_{t-i} + \epsilon_t, \]  

(1.28)

where \( \hat{u}_t \) and \( \hat{v}_t \) are the OLS residuals from the regressions of \( \Delta y_t \) and \( z_{t-1} \) on \( \Delta x_t, \Delta z_{t-1}, \Delta z_{t-2}, \ldots, \Delta z_{t-k+1} \).

Case II: (Restricted Intercepts; No Trends.) The structural VECM is

\[ \Delta y_t = \Pi_y \mu + \Pi_y z_{t-1} + \omega \Delta x_t + \sum_{i=1}^{k-1} \Gamma_i \Delta z_{t-i} + \epsilon_t, \]  

(1.29)

where \( \hat{u}_t \) and \( \hat{v}_t \) are the OLS residuals from the regressions of \( \Delta y_t \) and \( (l_T, z_{t-1}) \) on \( \Delta x_t, \Delta z_{t-1}, \Delta z_{t-2}, \ldots, \Delta z_{t-k+1} \). \( l_T \) is a \( T \times 1 \) vector of ones.

Case III: (Unrestricted Intercepts; No Trends.) The structural VECM is

\[ \Delta y_t = c_0 + \Pi_y z_{t-1} + \omega \Delta x_t + \sum_{i=1}^{k-1} \Gamma_i \Delta z_{t-i} + \epsilon_t, \]  

(1.30)

where \( \hat{u}_t \) and \( \hat{v}_t \) are the OLS residuals from the regressions of \( \Delta y_t \) and \( z_{t-1} \) on \( \Delta x_t, \Delta z_{t-1}, \Delta z_{t-2}, \ldots, \Delta z_{t-k+1} \) and a constant.

Case IV: (Unrestricted Intercepts; Restricted Trends.) The structural VECM is

\[ \Delta y_t = c_0 + \Pi_y \gamma t + \Pi_y z_{t-1} + \omega \Delta x_t + \sum_{i=1}^{k-1} \Gamma_i \Delta z_{t-i} + \epsilon_t, \]  

(1.31)

where \( \hat{u}_t \) and \( \hat{v}_t \) are the OLS residuals from the regressions of \( \Delta y_t \) and \( (\tau_T, z_{t-1}) \) on \( \Delta x_t, \Delta z_{t-1}, \Delta z_{t-2}, \ldots, \Delta z_{t-k+1} \) and a constant. \( \tau_T \) is the time trend with \( \tau_T \equiv (1, \ldots, T)' \). This is the case discussed in Section 1.3.1-1.3.3.

Case V: (Unrestricted Intercepts; Unrestricted Trends.) The structural VECM is

\[ \Delta y_t = c_0 + \Pi_y \gamma t + \Pi_y z_{t-1} + \omega \Delta x_t + \sum_{i=1}^{k-1} \Gamma_i \Delta z_{t-i} + \epsilon_t, \]  

(1.32)

where \( \hat{u}_t \) and \( \hat{v}_t \) are the OLS residuals from the regressions of \( \Delta y_t \) and \( z_{t-1} \) on \( \Delta x_t, \Delta z_{t-1}, \Delta z_{t-2}, \ldots, \Delta z_{t-k+1} \), a constant and a time trend.

The choice of deterministic variables is an important empirical question as
the above five cases imply very different trend behavior for series modelled. To illustrate, consider a simple bivariate system with no short-run dynamics and single cointegrating relation $\beta' z_t = y_t - \theta x_t$. The conditional and the marginal models are,

$$
\Delta y_t = (c_1 - \omega c_2) + (d_1 - \omega d_2)t + \alpha_1 (y_{t-1} - \theta x_{t-1}) \\
+ \omega \Delta x_t + (\epsilon_{yt} - \omega \epsilon_{xt}) \\
\text{(1.33)}
$$

$$
\Delta x_t = c_2 + d_2 t + \alpha_2 (y_{t-1} - \theta x_{t-1}) + \epsilon_{xt} \\
\text{(1.34)}
$$

When $\alpha_2 = 0$, $x_t$ is weakly exogenous for $\theta$, and the maximum likelihood estimator for $\theta$ is derived exclusively from the conditional model.

Suppose case V is chosen to represent the data generating process (DGP), $y_t$ then contains a quadratic trend because $\Delta y_t$ grows linearly. Harbo, Johansen, Nielsen, and Rahbek (1998) show that $-2 < \alpha_1 < 0$ the cointegrating vector $\beta' z_t = y_t - \theta x_t$ contains only a linear trend. This implies that the level of $x_t$ must share the same quadratic trend with $y_t$. That is, there exists only one independent quadratic trend. If, however, there is no cointegration between $y_t$ and $x_t$, the number of independent quadratic trends is two. Therefore, case V has an unpleasant implication that different trending behavior should follow for different values of the cointegrating rank $r$. The number of independent quadratic deterministic trends, $n-r$, decreases as $r$ increases. In contrast, if case IV is chosen to represent the DGP, there is a linear trend in $y_t$ as well as in the cointegrating relation $\beta' z_t = y_t - \theta x_t$, and quadratic trend is eliminated entirely. Any linear combination of $y_t$ and $x_t$ allows a linear trend. The deterministic trending behavior would be the same for different values of the cointegrating rank. A similar argument for the constant applies to case III versus case II.

Harbo, Johansen, Nielsen, and Rahbek (1998) prove that the asymptotic distribution of the likelihood ratio test for the cointegrating rank is free of nuisance parameters for cases I, II and IV, whereas for cases III and V the distribution contains a nuisance parameter making inference much more complicated. They therefore advocate modelling with restricted highest-order deterministic term. For
instance, instead of testing for cointegrating rank under case III, they recommend analyzing the slightly larger case IV and then use $\chi^2$ statistics to test for zero restrictions on the trend term in the cointegrating space. Pesaran, Shin, and Smith (2000) reach the same conclusion.

1.3.5 Hall’s Sequential System Reduction

The system in equation (1.26) is the general VECM with exogenous I(1) variables. It is rarely the final form, however, as significant simplification takes place to reduce the system to a parsimonious representation. Four types of restrictions are used,

1. Restrictions on the rank of long-run matrix ($\Pi$);
2. Restrictions on the short-run dynamic coefficients ($\Gamma_i$'s);
3. Restrictions on the long-run cointegrating vectors, $\beta$;
4. Restrictions on the loading parameters, $\alpha$.

Researchers have proposed different ways to impose these restrictions (Johansen 1988, 1991, 1995; Phillips 1991, 1995; Saikkonen 1993a, 1993b; Pesaran and Shin 2001). Hall, Henry, and Greenslade (2002) argue that these approaches are almost impossible to implement successfully when a fairly rich specification encounters a typical sample size. The interaction of dynamic and long-run parameters has enormous effects on the size and power of the statistical tests conventionally adopted. They conduct Monte Carlo simulation to reveal that imposing valid weak exogeneity restrictions before testing for the cointegrating rank generally improves the power of Johansen’s rank test. Nevertheless, restricting the cointegrating rank has little impact on the weak exogeneity test, at least as long as the rank is not restricted to be less than the true rank.

They suggest the following strategy in reducing a general VECM to the most parsimonious representation,
1. Make (and wherever possible test) weak exogeneity assumptions about the model;

2. Test the cointegrating rank;

3. Upon determination of the cointegrating rank, employ Johansen's reduced rank procedure to estimate the cointegrating vectors. These vectors enter the VECM in an unrestricted fashion, i.e., each equation has all the Johansen-based cointegrating vectors in it;

4. Follow Pesaran and Shin (2001) to impose long-run structural just (over) identifying restrictions on the $\beta$ vector.

5. Estimate the complete dynamic model and simplify the dynamics. At this stage, the causal structure of the model can be established by eliminating unnecessary cointegrating vectors from an equation based on likelihood ratio tests.

1.4 A Complete Hawaii Tourism Model.

The Hawaii tourism system under consideration has nine variables $z_t=(vus_{hi}, vjp_{hi}, prm_{hi}, ocup_{hi}, trms_{hi}, nir_{us}, cpi_{us}, nir_{jp}, p_{jp})$, among which $y_t=(vus_{hi}, vjp_{hi}, prm_{hi}, ocup_{hi}, trms_{hi})$ are endogenous and $x_t=(nir_{us}, cpi_{us}, nir_{jp}, p_{jp})$ are exogenous according to tourism demand and supply theories. This section applies recent advances in cointegration analysis discussed in the previous section to the Hawaii tourism model. The organization is as follows: Section 1.4.1 determines the order of integration of the series involved; Section 1.4.2 tests and imposes weak exogeneity restrictions; Section 1.4.3 establishes the cointegrating rank conditional on imposed weak exogeneity restrictions; Section 1.4.4 discusses the long-run cointegrating relations for the system; Section 1.4.5 reduces the model to the most parsimonious representation.
1.4.1 Unit Root Tests

In the literature, the most commonly used methodology to establish the order of integration of a series is to test for unit roots in the autoregressive processes using *Dickey-Fuller* (DF) and *augmented Dickey-Fuller* (ADF) tests (Dickey and Fuller, 1979, 1981). It has also been recognized that DF and ADF tests are sensitive to whether an intercept and/or a time trend is included. In addition, Schwert (1987) shows that unit root tests derived from pure autoregressive processes have different sampling distributions when the true process is a mixed autoregressive-integrated moving average (ARIMA) process. When the moving average parameter is close to 1, DF and ADF tests have true critical values that are far greater than the standard Dickey-Fuller distributions tabulated in Fuller (1976). That is, the DF and ADF tests tend to reject the null hypothesis of unit root too frequently.

I use both the ADF and Schwert tests for unit roots. Table 1.2 lists the standard DF and ADF test statistics when a constant and a trend are included in the specification. From the table, the null of unit root cannot be rejected for all variables in levels. When variables are first differenced, ADF test statistics reject the null of unit root for all except the Hawaii hotel room price, and the U.S. and Japan real income series. The Japanese price is borderline significant. Schwert’s (1987) test specifies the lag length in ADF type tests using the rules of thumb $l_4 = [4 \times (N/100)^{1/4}]$ and $l_{12} = [12 \times (N/100)^{1/4}]$ with $N$ being the total number of observations. For the Hawaii tourism model under discussion, $N = 86$, $l_4 = 4$ and $l_{12} = 12$. Table 1.3 reports the Schwert($l_4$) and Schwert($l_{12}$) test statistics both with and without a time trend. Readings from the table do not give consistent conclusions on the order of integration. When there is no time trend, the unit root hypothesis is rejected for all variables except $\Delta nir_{jp}$ at the 5% significance level with 4 lags in the specification. However, when the lag length is increased to 12, the unit root hypothesis is rejected only for $\Delta p_{jp}$. Results are similar when a time trend is included. From the $AR(1-5)$ LM test, 4 lags seem sufficient for all variables under consideration. I therefore accept Schwert($l_4$) test results and treat all variables except $\Delta nir_{jp}$ as I(1) series.
Table 1.2: Time Series Property of the Data – ADF Unit Root Test

DF: $\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \epsilon_t$

ADF: $\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \sum_{i=1}^{5} \delta_i \Delta y_{t-i} + \epsilon_t$

$H_0: \gamma = 0$

<table>
<thead>
<tr>
<th>Variables</th>
<th>DF</th>
<th>ADF(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>vus_hi</td>
<td>-2.087</td>
<td>-2.023</td>
</tr>
<tr>
<td>vjp_hi</td>
<td>-1.682</td>
<td>0.431</td>
</tr>
<tr>
<td>prm_hi</td>
<td>-1.265</td>
<td>-1.627</td>
</tr>
<tr>
<td>trms_hi</td>
<td>-1.957</td>
<td>-1.707</td>
</tr>
<tr>
<td>oocup_hi</td>
<td>-3.898</td>
<td>-2.184</td>
</tr>
<tr>
<td>cpi_us</td>
<td>-5.576</td>
<td>-1.226</td>
</tr>
<tr>
<td>nir_us</td>
<td>-1.868</td>
<td>-2.143</td>
</tr>
<tr>
<td>p_jp</td>
<td>-0.711</td>
<td>-1.283</td>
</tr>
<tr>
<td>nir_jp</td>
<td>0.465</td>
<td>-0.584</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Variables</th>
<th>DF</th>
<th>ADF(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta$vus_hi</td>
<td>-10.648</td>
<td>-3.525</td>
</tr>
<tr>
<td>$\Delta$vjp_hi</td>
<td>-14.079</td>
<td>-4.709</td>
</tr>
<tr>
<td>$\Delta$prm_hi</td>
<td>-11.601</td>
<td>-2.931</td>
</tr>
<tr>
<td>$\Delta$trms_hi</td>
<td>-7.298</td>
<td>-3.731</td>
</tr>
<tr>
<td>$\Delta$oocup_hi</td>
<td>-12.828</td>
<td>-4.138</td>
</tr>
<tr>
<td>$\Delta$cpi_us</td>
<td>-6.157</td>
<td>-4.461</td>
</tr>
<tr>
<td>$\Delta$nir_us</td>
<td>-8.482</td>
<td>-2.724</td>
</tr>
<tr>
<td>$\Delta$p_jp</td>
<td>-6.849</td>
<td>-3.364</td>
</tr>
<tr>
<td>$\Delta$nir_jp</td>
<td>-10.759</td>
<td>-2.588</td>
</tr>
</tbody>
</table>

Note: Column 1 gives the target series (dependent variable in equations DF and ADF): vus_hi and vjp_hi are U.S. and Japanese visitor arrivals to Hawaii; prm_hi, trms_hi and oocup_hi are respectively average hotel room rate, total hotel room stock and average hotel occupancy rate in Hawaii; cpi_us is U.S. CPI; nir_us and nir_jp are U.S. and Japan real personal incomes; p_jp is exchange rate adjusted Japanese CPI. Column 2 is the Dick-Fuller test statistic for $H_0$. Column 3 is the Augmented Dick-Fuller statistic for $H_0$. All variables except oocup_hi are in logarithms. Boldness indicates significance at 5% level where critical value is -3.45.
Table 1.3: Time Series Property of the Data – Schwert Unit Root Test

\[ \Delta y_t = \alpha + \gamma y_{t-1} + \sum_{i=1}^{k} \delta_i \Delta y_{t-k} + \epsilon_t \]

\[ k = 4 \text{ for Schwert}(l_4) \text{ and } k = 12 \text{ for Schwert}(l_{12}) \]

\( H_0 : \gamma = 0 \)

<table>
<thead>
<tr>
<th>Variables</th>
<th>MA</th>
<th>Schwert((l_4))</th>
<th>CV((l_4))</th>
<th>AR(1-5)</th>
<th>Schwert((l_{12}))</th>
<th>CV((l_{12}))</th>
<th>AR(1-5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\Delta vus_hi)</td>
<td>-0.23</td>
<td><strong>-4.076</strong></td>
<td>-2.87</td>
<td>0.7652</td>
<td><strong>-2.016</strong></td>
<td>-2.82</td>
<td>0.4837</td>
</tr>
<tr>
<td>(\Delta vjp_hi)</td>
<td>-0.31</td>
<td><strong>-4.865</strong></td>
<td>-2.93</td>
<td>0.3567</td>
<td>-1.341</td>
<td>-2.85</td>
<td>0.7987</td>
</tr>
<tr>
<td>(\Delta prm_hi)</td>
<td>-0.20</td>
<td><strong>-3.434</strong></td>
<td>-2.87</td>
<td>0.9657</td>
<td>-1.813</td>
<td>-2.82</td>
<td>0.5255</td>
</tr>
<tr>
<td>(\Delta trms_hi)</td>
<td>0.24</td>
<td><strong>-3.959</strong></td>
<td>-2.87</td>
<td>0.1901</td>
<td>-1.856</td>
<td>-2.82</td>
<td>0.4065</td>
</tr>
<tr>
<td>(\Delta ocup_hi)</td>
<td>-0.37</td>
<td><strong>-5.348</strong></td>
<td>-2.93</td>
<td>0.8226</td>
<td>-1.867</td>
<td>-2.85</td>
<td>0.3811</td>
</tr>
<tr>
<td>(\Delta nir_us)</td>
<td>0.33</td>
<td><strong>-3.724</strong></td>
<td>-3.02</td>
<td>0.0874</td>
<td>-2.132</td>
<td>-2.82</td>
<td>0.1846</td>
</tr>
<tr>
<td>(\Delta cpi_us)</td>
<td>0.83</td>
<td><strong>-4.516</strong></td>
<td>-4.38</td>
<td>0.1845</td>
<td>-1.746</td>
<td>-2.92</td>
<td>0.2796</td>
</tr>
<tr>
<td>(\Delta nir_jp)</td>
<td>0</td>
<td>-1.758</td>
<td>-2.87</td>
<td>0.8874</td>
<td>-1.068</td>
<td>-2.82</td>
<td>0.4947</td>
</tr>
<tr>
<td>(\Delta p_jp)</td>
<td>0.35</td>
<td><strong>-3.389</strong></td>
<td>-3.02</td>
<td>0.9894</td>
<td><strong>-2.872</strong></td>
<td>-2.82</td>
<td>0.5615</td>
</tr>
</tbody>
</table>

Note: Column 1 lists the series tested; Column 2 gives the MA parameter of the series; Column 3 and 6 are the Schwert\((l_4)\) and Schwert\((l_{12})\) test statistics; Column 4 and 7 list the 5% critical values for Schwert\((l_4)\) and Schwert\((l_{12})\) tabulated in Table 7 of Schwert (1987) for the corresponding MA parameter. For instance, the estimated MA coefficient for \(\Delta vus\_hi\) is -0.23, the closest case in Schwert (1987) has MA parameter of 0. The corresponding critical values are -2.87 for Schwert\((l_4)\) and -2.82 for Schwert\((l_{12})\) without a time trend, and -3.41 for Schwert\((l_4)\) and -3.36 for Schwert\((l_{12})\) with a time trend; Column 5 and 8 list the p-values of LM test for residual serial correlation with lags 1-5. All variables except \(ocup\_hi\) are in logarithms. Boldness indicates significance at 5%.

\[ \Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \sum_{i=1}^{k} \delta_i \Delta y_{t-k} + \epsilon_t \]

\[ k = 4 \text{ for Schwert}(l_4) \text{ and } k = 12 \text{ for Schwert}(l_{12}) \]

\( H_0 : \gamma = 0 \)

<table>
<thead>
<tr>
<th>Variables</th>
<th>MA</th>
<th>Schwert((l_4))</th>
<th>CV((l_4))</th>
<th>AR(1-5)</th>
<th>Schwert((l_{12}))</th>
<th>CV((l_{12}))</th>
<th>AR(1-5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\Delta vus_hi)</td>
<td>-0.23</td>
<td><strong>-4.267</strong></td>
<td>-3.41</td>
<td>0.6809</td>
<td>-1.956</td>
<td>-3.36</td>
<td>0.4416</td>
</tr>
<tr>
<td>(\Delta vjp_hi)</td>
<td>-0.31</td>
<td><strong>-5.389</strong></td>
<td>-3.49</td>
<td>0.7867</td>
<td>-2.305</td>
<td>-3.36</td>
<td>0.8646</td>
</tr>
<tr>
<td>(\Delta prm_hi)</td>
<td>-0.2</td>
<td><strong>-3.593</strong></td>
<td>-3.41</td>
<td>0.9856</td>
<td>-2.293</td>
<td>-3.36</td>
<td>0.4191</td>
</tr>
<tr>
<td>(\Delta trms_hi)</td>
<td>0.24</td>
<td><strong>-4.556</strong></td>
<td>-3.41</td>
<td>0.1836</td>
<td>-2.863</td>
<td>-3.36</td>
<td>0.7987</td>
</tr>
<tr>
<td>(\Delta ocup_hi)</td>
<td>-0.37</td>
<td><strong>-5.440</strong></td>
<td>-3.49</td>
<td>0.7893</td>
<td>-1.912</td>
<td>-3.36</td>
<td>0.2618</td>
</tr>
<tr>
<td>(\Delta nir_us)</td>
<td>0.33</td>
<td><strong>-3.641</strong></td>
<td>-3.61</td>
<td>0.0706</td>
<td>-2.151</td>
<td>-3.36</td>
<td>0.1915</td>
</tr>
<tr>
<td>(\Delta cpi_us)</td>
<td>0.83</td>
<td><strong>-4.404</strong></td>
<td>-5.09</td>
<td>0.2237</td>
<td>-1.869</td>
<td>-3.49</td>
<td>0.1697</td>
</tr>
<tr>
<td>(\Delta nir_jp)</td>
<td>0</td>
<td>-2.758</td>
<td>-3.41</td>
<td>0.8310</td>
<td>-3.023</td>
<td>-3.36</td>
<td>0.6757</td>
</tr>
<tr>
<td>(\Delta p_jp)</td>
<td>0.35</td>
<td><strong>-3.525</strong></td>
<td>-3.61</td>
<td>0.8925</td>
<td>-3.563</td>
<td>-3.36</td>
<td>0.3257</td>
</tr>
</tbody>
</table>
A closer look at $\Delta \text{nir}_{-} \text{jp}$ suggests that the non-rejection of the unit root hypothesis is due to a slowdown in the growth of Japanese real income during the 1990s. Japanese real income growth averaged 1.2% during the 1980s, followed by zero growth for the 1990s (see figure 1.1). Perron (1989, 1990) argued that a structural change in the mean of a stationary variable tends to bias the usual unit root tests towards non-rejection of the null of unit root. I therefore perform the Perron (1990) test for a unit root on $\Delta \text{nir}_{-} \text{jp}$. I pick the break point to be 1991Q1 because the Japanese economy peaked in February 1991 according to the Economic Planning Agency (EPA). The null hypothesis in the Perron test is that of a non-stationary process,

\begin{equation}
H_0 : \quad y_t = \alpha + \gamma P_t + y_{t-1} + \epsilon_t, \tag{1.35}
\end{equation}

where

\[ P_t = \begin{cases} 
1 & \text{if } t = 1991Q1, \\
0 & \text{otherwise.}
\end{cases} \]

and the alternative hypothesis is that of a stationary process subject to a shift,

\begin{equation}
H_1 : \quad y_t = \mu + \delta S_t + \epsilon_t, \tag{1.36}
\end{equation}

where

\[ S_t = \begin{cases} 
1 & \text{if } t \geq 1991Q1, \\
0 & \text{otherwise.}
\end{cases} \]

The Perron test is a two-stage procedure. First, OLS residuals ($\epsilon_t$) from the regression under the alternative hypothesis are computed as,

\[ e_t = y_t - \hat{\mu} - \hat{\delta} S_t, \]
If the alternative hypothesis represented by equation (1.36) is true, the OLS regression should yield residuals that are purged of the intervention so that accepting the stationarity of the residuals favors the alternative hypothesis. If, however, the residuals are found to be non-stationary, the evidence is in favor of the null hypothesis represented by equation (1.35). Hence, to test the order of integration of the series, the residuals are used in the second stage regression,

\[ e_t = \omega P_t + \theta e_{t-1} + \nu_t, \]

or equivalently,

\[ \Delta e_t = \omega P_t + \phi e_{t-1} + \nu_t, \]  \hspace{1cm} (1.37)

where \( \phi = \theta - 1 \). The second stage regression in (1.37) may be augmented by lags of the dependent variable to whiten regression errors. The test for the stationarity of residuals is simply whether regression estimate of \( \phi \) in (1.37) is significantly negative. The Perron test is applied to the first difference of Japanese real income series \( \Delta nir_{jp} \). The estimated regression coefficient on \( e_{t-1} \) is -3.625 which is below the critical value -3.45 for ADF(3) unit root test. I therefore conclude that \( \Delta nir_{jp} \) is stationary with a structural break. All variables used in the Hawaii tourism model are I(1). Figures 1.2 to 1.4 plot the series both in levels and first differences.

### 1.4.2 Weak Exogeneity

The theoretical review of tourism demand and supply indicates that four out of the nine variables are weakly exogenous: U.S. real income (nir_us), U.S. CPI (cpi_us), Japanese real income (nir_jp) and the exchange rate adjusted Japanese CPI (p_jp). To formally test these restrictions, I set a row in the loading matrix to zero, i.e., \( \alpha_x = 0 \) (see section 1.3.3). Statistically this has the effect of excluding all cointegrating vectors from equations corresponding to the "theoretically" exogenous variables, i.e., cointegrating vectors do not explain variations in the first
Figure 1.1: Growth in Japanese Real National Income 1980Q1-2001Q2
Figure 1.2: Variables in the Hawaii Tourism Model
Figure 1.3: Variables in the Hawaii Tourism Model—Continued
Figure 1.4: Variables in the Hawaii Tourism Model—Continued
Table 1.4: Weak Exogeneity Test ($\alpha_x = 0$)

<table>
<thead>
<tr>
<th></th>
<th>Weak Exogeneity Test</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\chi^2$</td>
<td></td>
<td>$p$-value</td>
</tr>
<tr>
<td>A) eight cointegrating vectors</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>nir.us</td>
<td>14.14</td>
<td></td>
<td>0.0781</td>
</tr>
<tr>
<td>cpi.us</td>
<td>42.70</td>
<td></td>
<td>0.0000</td>
</tr>
<tr>
<td>nir.jp</td>
<td>41.78</td>
<td></td>
<td>0.0000</td>
</tr>
<tr>
<td>p.jp</td>
<td>12.60</td>
<td></td>
<td>0.1264</td>
</tr>
<tr>
<td>B) six cointegrating vectors, nir.us and p.jp exogenous</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>cpi.us</td>
<td>40.53</td>
<td></td>
<td>0.0000</td>
</tr>
<tr>
<td>p.jp</td>
<td>38.37</td>
<td></td>
<td>0.0000</td>
</tr>
<tr>
<td>C) three cointegrating vectors</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>nir.us</td>
<td>1.78</td>
<td></td>
<td>0.6198</td>
</tr>
<tr>
<td>cpi.us</td>
<td>15.19</td>
<td></td>
<td>0.0017</td>
</tr>
<tr>
<td>nir.jp</td>
<td>22.17</td>
<td></td>
<td>0.0001</td>
</tr>
<tr>
<td>p.jp</td>
<td>4.81</td>
<td></td>
<td>0.1860</td>
</tr>
<tr>
<td>D) six cointegrating vectors, nir.us and p.jp exogenous</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>cpi.us</td>
<td>20.52</td>
<td></td>
<td>0.0001</td>
</tr>
<tr>
<td>p.jp</td>
<td>26.74</td>
<td></td>
<td>0.0000</td>
</tr>
</tbody>
</table>

Note: Column 1 lists the variables tested; Column 2 gives the $\chi^2$ statistics and column 3 is the corresponding probability values for the test. Bold entries indicate significance at 5\% level.

differences of exogenous variables. The $\chi^2$ statistic and corresponding $p$-values are listed in table 1.4.

For a system with nine variable, there can exist at the most eight cointegrating vectors. Weak exogeneity under the assumption of eight cointegrating vectors is rejected for cpi.us and nir.jp at 5\% level, but not for nir.us or p.jp. The literature has found that weak exogeneity depends on model specification and suggested exogenizing the non-rejecting variables and re-test weak exogeneity for the remaining variables. I therefore treat nir.us and p.jp as weakly exogenous and
re-estimate the system with seven endogenous variables, two exogenous variable and six cointegrating vectors. The test statistic still strongly rejects the weak exogeneity of \textit{cpi.us} and \textit{nir.jp} at 5\% significance level. When three cointegrating relations are assumed (as depicted by equations (1.23)-(1.25)), the results are unchanged.

By setting $\alpha_x = 0$, we implicitly assume that variables in the $x_t$ vector ($\textit{nir.us}$, $\textit{cpi.us}$, $\textit{nir.jp}$, $\textit{p.jp}$) are not cointegrated among themselves. For the Hawaii tourism model, however, it is highly like that these exogenous variables are cointegrated. Using a restricted trend, unrestricted intercept VAR(5) specification, I can not reject the hypothesis that there is at least one cointegrating relation among the four variables. Therefore, the rejection of $\alpha_x = 0$ is likely due to cointegration among exogenous variables, not to their endogeneity. According to Harbo, Johansen, Nielsen, and Rahbek (1998), weak exogeneity under such circumstances can be tested by estimating the conditional model with assumed exogeneity and insert the estimated cointegrating vectors back into the marginal model. Weak exogeneity is established by statistical insignificance of the cointegrating vectors in the marginal model.

The Harbo \textit{et. al.} exogeneity test requires fully specified cointegrating vectors and can only be performed after the cointegrating vectors are identified. I present the test statistics in this section, although the identified cointegrating vectors are not presented until section 1.4.4. To perform the test, the first differences of exogenous variables ($\Delta \textit{nir.us}$, $\Delta \textit{cpi.us}$, $\Delta \textit{nir.jp}$ and $\Delta \textit{p.jp}$) are each regressed on the current and lagged first differences of all variables, the three identified cointegrating vectors and a constant. Weak exogeneity test amounts to a joint $F$-test that coefficients on all three cointegrating vectors are zero. The test results are listed in table 1.5. As expected, weak exogeneity is not rejected for any of the variables.
Table 1.5: Harbo et. al. Weak Exogeneity Test

<table>
<thead>
<tr>
<th>Variables</th>
<th>F-test</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>nir_us</td>
<td>0.20</td>
<td>0.90</td>
</tr>
<tr>
<td>cpi_us</td>
<td>1.24</td>
<td>0.31</td>
</tr>
<tr>
<td>nir_jp</td>
<td>2.09</td>
<td>0.12</td>
</tr>
<tr>
<td>p_jp</td>
<td>0.37</td>
<td>0.78</td>
</tr>
</tbody>
</table>

Note: Column 1 lists the variables studied; Column 2 presents the F-test statistics and column 3 are the corresponding critical values.

Table 1.6: Cointegration Rank Statistics

| Hr | LR(H_r|H_n) Statistic | 0.05CV | 0.10CV | LR(H_r|H_r+1) Statistic | 0.05CV | 0.10CV |
|----|------------------|--------|--------|-----------------------|--------|--------|
|    |                   |        |        |                       |        |        |
| r  = 0 | 197.6        | 130.6  | 125.1  | 56.51                 | 49.76  | 46.74  |
| r  ≤ 1 | 141.1        | 99.11  | 93.98  | 54.76                 | 43.75  | 41.01  |
| r  ≤ 2 | 86.29        | 69.84  | 65.90  | 40.88                 | 37.44  | 34.66  |
| r  ≤ 3 | 45.41        | 45.10  | 41.57  | 28.15                 | 30.55  | 27.86  |
| r  ≤ 4 | 17.25        | 23.17  | 20.73  | 17.25                 | 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; 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; Bolded numbers indicate significance at 5% level.

1.4.3 Cointegrating Rank

Having established the weak exogeneity of nir_us, cpi_us, nir_jp and p_jp, I test for the cointegrating rank using Johansen's reduced rank methodology. Table 1.6 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, Shin, and Smith (2000) with four exogenous variables.

From the table, the null of zero, one, and two cointegrating relations are rejected at both the 5% and 10% levels. When it comes to the null of three cointegrating vectors, the trace statistic rejects at both 5% and 10% significance levels (though the rejection at 5% is borderline). Nevertheless, the maximum eigenvalue statistic
rejects the null at 10% level, but not at 5% level. I therefore conclude that the system has three long-run cointegrating vectors.

1.4.4 Long-run Cointegrating Vectors

Denote the three cointegrating vectors associated with 
\( z_t = (vus_{hi}, vjp_{hi}, \text{prm}_{hi}, \text{ocup}_{hi}, \text{trms}_{hi}, \text{nirus}, \text{cpius}, \text{nir}_{jp}, p_{jp}, t)' \) by \( \beta_1^*, \beta_2^*, \) and \( \beta_3^* \). Assuming they explain U.S. tourism demand, Japanese tourism demand and Hawaii tourism supply respectively, the table below lists the unrestricted cointegrating vectors.

<table>
<thead>
<tr>
<th>( vus_{hi} )</th>
<th>( vjp_{hi} )</th>
<th>( \text{prm}_{hi} )</th>
<th>( \text{ocup}_{hi} )</th>
<th>( \text{trms}_{hi} )</th>
<th>( \text{nirus} )</th>
<th>( \text{cpius} )</th>
<th>( \text{nir}_{jp} )</th>
<th>( p_{jp} )</th>
<th>( t )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \beta_1^* )</td>
<td>( \beta_{11} )</td>
<td>( \beta_{21} )</td>
<td>( \beta_{31} )</td>
<td>( \beta_{41} )</td>
<td>( \beta_{51} )</td>
<td>( \beta_{61} )</td>
<td>( \beta_{71} )</td>
<td>( \beta_{81} )</td>
<td>( \beta_{91} )</td>
</tr>
<tr>
<td>( \beta_2^* )</td>
<td>( \beta_{12} )</td>
<td>( \beta_{22} )</td>
<td>( \beta_{32} )</td>
<td>( \beta_{42} )</td>
<td>( \beta_{52} )</td>
<td>( \beta_{62} )</td>
<td>( \beta_{72} )</td>
<td>( \beta_{82} )</td>
<td>( \beta_{92} )</td>
</tr>
<tr>
<td>( \beta_3^* )</td>
<td>( \beta_{13} )</td>
<td>( \beta_{23} )</td>
<td>( \beta_{33} )</td>
<td>( \beta_{43} )</td>
<td>( \beta_{53} )</td>
<td>( \beta_{63} )</td>
<td>( \beta_{73} )</td>
<td>( \beta_{83} )</td>
<td>( \beta_{93} )</td>
</tr>
</tbody>
</table>

Exact identification, requiring three restrictions per vector, is accomplished by imposing two exclusion restrictions and one normalization restriction. Specifically, we exclude Japanese real income and Japanese visitor arrivals from the U.S. demand relation and normalize on U.S. visitor arrivals; exclude U.S. real income and U.S. visitor arrivals from the Japanese demand relation and normalize on Japanese visitor arrivals; exclude both real income variables from the Hawaii tourism supply relation and normalize on Hawaii room price. The table below shows these restrictions.

<table>
<thead>
<tr>
<th>( vus_{hi} )</th>
<th>( vjp_{hi} )</th>
<th>( \text{prm}_{hi} )</th>
<th>( \text{ocup}_{hi} )</th>
<th>( \text{trms}_{hi} )</th>
<th>( \text{nirus} )</th>
<th>( \text{cpius} )</th>
<th>( \text{nir}_{jp} )</th>
<th>( p_{jp} )</th>
<th>( t )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \beta_1^* )</td>
<td>1</td>
<td>0</td>
<td>( \beta_{31} )</td>
<td>( \beta_{41} )</td>
<td>( \beta_{51} )</td>
<td>( \beta_{61} )</td>
<td>( \beta_{71} )</td>
<td>0</td>
<td>( \beta_{91} )</td>
</tr>
<tr>
<td>( \beta_2^* )</td>
<td>0</td>
<td>1</td>
<td>( \beta_{32} )</td>
<td>( \beta_{42} )</td>
<td>( \beta_{52} )</td>
<td>0</td>
<td>( \beta_{72} )</td>
<td>( \beta_{82} )</td>
<td>( \beta_{92} )</td>
</tr>
<tr>
<td>( \beta_3^* )</td>
<td>( \beta_{13} )</td>
<td>( \beta_{23} )</td>
<td>1</td>
<td>( \beta_{43} )</td>
<td>( \beta_{53} )</td>
<td>0</td>
<td>( \beta_{73} )</td>
<td>0</td>
<td>( \beta_{93} )</td>
</tr>
</tbody>
</table>

This is the exactly identified system and serves as the basis for over-identifying restrictions. The estimated cointegrating vectors are shown in the table below, with asymptotic standard errors in parentheses. The value of the log-likelihood function for the just identified system is \( LL_E = 1682.65 \). Asymptotic standard
errors are given in parentheses.\(^8\)

<table>
<thead>
<tr>
<th>(vus_{hi})</th>
<th>(vjp_{hi})</th>
<th>(prm_{hi})</th>
<th>(ocup_{hi})</th>
<th>(trms_{hi})</th>
<th>(nir_{us})</th>
<th>(cpi_{us})</th>
<th>(nir_{jp})</th>
<th>(p_{jp})</th>
<th>(t)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\beta_1^*)</td>
<td>1</td>
<td>0</td>
<td>0.14</td>
<td>1.60</td>
<td>35.54</td>
<td>-36.13</td>
<td>-47.50</td>
<td>0</td>
<td>-0.12</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(3.90)</td>
<td>(4.09)</td>
<td>(8.10)</td>
<td>(9.12)</td>
<td>(12.47)</td>
<td>(0.95)</td>
<td>(0.13)</td>
</tr>
<tr>
<td>(\beta_2^*)</td>
<td>0</td>
<td>1</td>
<td>0.88</td>
<td>-2.13</td>
<td>3.79</td>
<td>0</td>
<td>-0.12</td>
<td>-6.07</td>
<td>0.55</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.76)</td>
<td>(0.70)</td>
<td>(1.37)</td>
<td>(1.84)</td>
<td>(1.45)</td>
<td>(0.21)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>(\beta_3^*)</td>
<td>-0.25</td>
<td>-0.23</td>
<td>1</td>
<td>-0.73</td>
<td>-1.12</td>
<td>0</td>
<td>1.04</td>
<td>0</td>
<td>0.09</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.09)</td>
<td>(0.08)</td>
<td>(0.20)</td>
<td>(0.35)</td>
<td>(0.38)</td>
<td>(0.06)</td>
<td>(0.002)</td>
</tr>
</tbody>
</table>

The three final cointegrating vectors to be identified are,

\[
vus_{hi} = \beta_{01} * t + \beta_{61} * nir_{us} + \beta_{71} * cpi_{us} + \beta_{61} * cpi_{us} + \beta_{31} * prm_{hi} + e_{us}, \tag{1.38}
\]

\[
vjp_{hi} = \beta_{02} * t + \beta_{82} * nir_{jp} + \beta_{92} * p_{jp} + \beta_{32} * prm_{hi} + e_{jp}, \tag{1.39}
\]

\[
prm_{hi} = \beta_{03} * t + \beta_{13} * (vus_{hi} + vjp_{hi}) + \beta_{43} * ocup_{hi} \\
+ \beta_{73} * cpi_{us} + \beta_{53} * trms_{hi} + e_{prm}. \tag{1.40}
\]

All equations are over-identified. Based on the exact-identifying restrictions, I test the following over-identifying restrictions using the long-run structural modelling techniques suggested in Pesaran and Shin (2001).

Equation (1.38): \(\beta_{41} = \beta_{51} = \beta_{91} = 0, \beta_{31} = -\beta_{71}\);

Equation (1.39): \(\beta_{42} = \beta_{52} = \beta_{72} = 0, \beta_{32} = -\beta_{92}\);

Equation (1.40): \(\beta_{93} = 0, \beta_{13} = \beta_{23}\).

**U.S. Tourism Demand**

To identify a U.S. tourism demand relation, I test the four over-identifying restrictions specified above, i.e., three exclusion restrictions \(\beta_{41} = \beta_{51} = \beta_{91} = 0\) (corresponding to \(ocup_{hi}, trms_{hi}\) and \(p_{jp}\)), and the homogeneity restriction \(\beta_{31} = -\beta_{71}\) (parameters on \(prm_{hi}\) and \(cpi_{us}\) are equal in size but opposite in sign). 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

\(^8\)Computation results reported in this section are carried out using *Pc-Fiml 9.10.*
of fourteen models from four studies, they report a median income elasticity of 2.4. In a separate study, 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. I therefore restrict the income elasticity ($\beta_{61}$) to be 2.5 initially. With these five over-identifying restrictions, the estimated cointegrating vectors are given by

\[
\begin{array}{ccccccccccc}
& vus_{hi} & vjp_{hi} & prn_{hi} & ocup_{hi} & trms_{hi} & nir_{us} & cpi_{us} & nir_{jp} & p_{jp} & t \\
\beta_1^* & 1 & 0 & 0.11 & 0 & 0 & -2.50 & -0.11 & 0 & 0 & 0.01 \\
& & & & & & & & & & (0.33) \\
\beta_2^* & 0 & 1 & -2.91 & 1.75 & 6.55 & 0 & -5.82 & -1.75 & -0.13 & 0.07 \\
& & & & & & & & & & (0.65) (0.71) (1.24) (1.72) (1.15) (0.20) (0.01) \\
\beta_3^* & -0.35 & -0.24 & 1 & -0.77 & -0.84 & 0 & 0.71 & 0 & 0.10 & -0.01 \\
& & & & & & & & & & (0.07) (0.07) (0.19) (0.31) (0.38) (0.05) (0.002)
\end{array}
\]

The (log-) likelihood ratio test has value 13.59 and a p-value of 1.84% for $\chi^2(5)$ distribution. These over-identifying restrictions are therefore rejected at the 5% significance level, but not at 1% level. Edwards (1995) obtains an income elasticity of 5 for U.S. travellers to Asia-Pacific region. To study the impacts of different values for income elasticity, I set the value to 3, 4 and 5 respectively. The resulting price elasticities are -0.32, -0.73, and -1.16, with p-values 3.18%, 6.64% and 10.13%. The price elasticity increases when the income elasticity rises, but the change is small. I therefore set income elasticity to 5 to be consistent with Edwards (1995). The estimated U.S. demand relation ($\beta_1^*$) given below and all parameter estimates have theoretically correct signs:

**Japanese Tourism demand**

A Japanese demand relation is harder to identify. I initially employ restrictions similar to those used in the U.S. tourism demand. The income elasticity of Japanese visitors are left unrestricted as there is no indication in the literature
of a good estimate. Altogether four over-identifying restrictions are applied: three exclusion restrictions on \( \text{ocup}_{hi} \), \( \text{trms}_{hi} \), and \( \text{cpi}_{us} \) (\( \beta_{42} = \beta_{52} = \beta_{72} = 0 \)) and one homogeneity restriction on \( \text{prm}_{hi} \) and \( \text{p}_{jp} \) (\( \beta_{32} = -\beta_{92} \)). With these restrictions, I obtain a \( \chi^2(4) \) statistic of 15.68 and a p-value of 0.35%. The restrictions are strongly rejected.

The literature has found very different responses of tourism demand to movements in exchange rate than to consumer prices. The first modification to the Japanese demand relation, therefore, is to break the price homogeneity assumption. This leads to a \( \chi^2(3) \) statistic of 8.50 and a p-value of 3.68%. The remaining restrictions are rejected at 5% significance level, but not the 1% level.

To relax one step further, I re-include \( \text{trsm}_{hi} \) in the cointegrating space. Empirically this is justified by the “You build, I come” mentality of travellers, especially travellers to foreign countries in pursuit of exotic experiences. When this is done, the \( \chi^2(2) \) reduces to 2.32 with a p-value of 31.33%. We do not reject the two restrictions at 5% significance level. A closer look at the estimated vector reveals that the time trend \( (t) \) can be safely excluded. The final three restrictions have \( \chi^2(3) \) statistic at 2.35 and a p-value of 50%. The estimated vector \( (\beta^*_3) \) and corresponding standard errors are listed in the table below.

<table>
<thead>
<tr>
<th>( vus_{hi} )</th>
<th>( vjp_{hi} )</th>
<th>( prm_{hi} )</th>
<th>( ocup_{hi} )</th>
<th>( trms_{hi} )</th>
<th>( nir_{us} )</th>
<th>( cpi_{us} )</th>
<th>( nir_{jp} )</th>
<th>( p_{jp} )</th>
<th>( t )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \beta_1^* )</td>
<td>1</td>
<td>0</td>
<td>1.16</td>
<td>0</td>
<td>0</td>
<td>-5</td>
<td>-1.16</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \beta_2^* )</td>
<td>0</td>
<td>1</td>
<td>-2.76</td>
<td>0.74</td>
<td>7.96</td>
<td>0</td>
<td>-6.31</td>
<td>-2.86</td>
<td>0.056</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.73)</td>
<td>(0.75)</td>
<td>(1.38)</td>
<td></td>
<td>(1.9)</td>
<td>(1.36)</td>
<td>(0.22)</td>
</tr>
<tr>
<td>( \beta_3^* )</td>
<td>-0.23</td>
<td>-0.23</td>
<td>1</td>
<td>-0.75</td>
<td>-1.16</td>
<td>0</td>
<td>1.10</td>
<td>0</td>
<td>0.09</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.08)</td>
<td>(0.07)</td>
<td>(0.19)</td>
<td>(0.33)</td>
<td>(0.38)</td>
<td></td>
<td>(0.06)</td>
</tr>
</tbody>
</table>

Empirically this is justified by the “You build, I come” mentality of travellers, especially travellers to foreign countries in pursuit of exotic experiences. When this is done, the \( \chi^2(2) \) reduces to 2.32 with a p-value of 31.33%. We do not reject the two restrictions at 5% significance level. A closer look at the estimated vector reveals that the time trend \( (t) \) can be safely excluded. The final three restrictions have \( \chi^2(3) \) statistic at 2.35 and a p-value of 50%. The estimated vector \( (\beta^*_3) \) and corresponding standard errors are listed in the table below.
The coefficient estimate on the room stock variable is negative and contrary to expectations. One explanation might come from the special sample period under study. The sample period chosen is 1980Q1 to 2001Q2. During this time, Hawaii experienced an economic cycle brought about by the booming, over-heating and eventual collapsing of the Japanese economy. Between 1985 and 1995, Japanese invested no less than $12 billion in Hawaii compared with a total of $850 million in the preceding 10 years. Total visitor plant inventory correspondingly increased from roughly 65,000 transient rental accommodations in the years 1985-87 to nearly 74,000 by the end of 1993. With the bust of Japanese economic bubble, visitor counts from the country dropped. But the hotel accommodation infrastructure, once installed, takes time to diminish. Statistically this may show as a negative correlation. Apart from the room stock, $p_{.jp}$ has the wrong sign. A rise in Japanese exchange-rate adjusted price level increases the competitiveness of Hawaii travel and the variable should have a positive sign. However, the estimated parameter is negative.

**Hawaii Tourism Supply**

The Hawaii tourism supply relation has two over-identifying restrictions: exclusion restriction on $p_{.jp}$ ($\beta_3 = 0$) and an equal parameter restriction on U.S. and Japanese arrival counts ($\beta_1 = \beta_2$). When imposed, the long-run cointegrating relations becomes:

<table>
<thead>
<tr>
<th>$vus_{hi}$</th>
<th>$vjp_{hi}$</th>
<th>$prm_{hi}$</th>
<th>$ocup_{hi}$</th>
<th>$trs_{hi}$</th>
<th>$nir_{us}$</th>
<th>$cpi_{us}$</th>
<th>$nir_{jp}$</th>
<th>$p_{.jp}$</th>
<th>$t$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_1^*$</td>
<td>1</td>
<td>0</td>
<td>-2.88</td>
<td>1.33</td>
<td>52.3</td>
<td>-44.3</td>
<td>-67.9</td>
<td>0</td>
<td>0.63</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(4.86)</td>
<td>(5.30)</td>
<td>(10.2)</td>
<td>(11.08)</td>
<td>(15.50)</td>
<td>(1.14)</td>
<td>(0.16)</td>
</tr>
<tr>
<td>$\beta_2^*$</td>
<td>0</td>
<td>1</td>
<td>0.14</td>
<td>-2.13</td>
<td>5.49</td>
<td>0</td>
<td>-2.04</td>
<td>-5.9</td>
<td>0.68</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.82)</td>
<td>(0.84)</td>
<td>(1.61)</td>
<td></td>
<td>(2.12)</td>
<td>(1.59)</td>
<td>(0.23)</td>
</tr>
<tr>
<td>$\beta_3^*$</td>
<td>-0.17</td>
<td>-0.17</td>
<td>1</td>
<td>-0.49</td>
<td>-1.56</td>
<td>0</td>
<td>1.58</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.06)</td>
<td>(0.19)</td>
<td>(0.32)</td>
<td></td>
<td>(0.34)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

---


10It is acknowledged that the structural break identified in the Japanese income series ($nir_{.jp}$) may have contributed to the weak demand cointegration relation for Japanese visitors.
The $\chi^2(2)$ statistic associated with the test is 1.54 and well below the 5% critical value. The supply restrictions are not rejected. Nevertheless, the estimated parameter on $cpi_{us}$ has the wrong sign. U.S. CPI in the supply relation supposedly approximates hotel operating cost. Theory prescribes a positive relationship between cost and price of final product—a markup over cost. Obviously the approximation is far less than satisfactory. The U.S. CPI may very well be excluded from the supply relation. Apart from this, the coefficient on $trms_{hi}$ does not have the correct sign either. A rise in hotel room stock should increase accommodation availability and puts downward pressure on the average room rate. However, the estimated coefficient is positive.

**Joint Restrictions**

Finally, I combine all three hypotheses and perform a joint test. The log-likelihood ratio statistic for the joint test has value 21.15, which is below the 1% critical level of $\chi^2(10)$ distribution. I do not reject the joint hypotheses of two demand and one supply relations. The parameter estimates of the joint test change only slightly from those of individual tests.

<table>
<thead>
<tr>
<th>vus_{hi}</th>
<th>vjp_{hi}</th>
<th>prn_{hi}</th>
<th>ocup_{hi}</th>
<th>trms_{hi}</th>
<th>nir_{us}</th>
<th>cpi_{us}</th>
<th>nir_{jp}</th>
<th>p_{jp}</th>
<th>t</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_1^*$</td>
<td>1</td>
<td>0</td>
<td>1.2</td>
<td>0</td>
<td>0</td>
<td>-5</td>
<td>-1.2</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>$\beta_2^*$</td>
<td>0</td>
<td>1</td>
<td>0.23</td>
<td>0</td>
<td>3.42</td>
<td>0</td>
<td>0</td>
<td>-5.2</td>
<td>0.31</td>
</tr>
<tr>
<td>$\beta_3^*$</td>
<td>-0.15</td>
<td>-0.15</td>
<td>1</td>
<td>-0.86</td>
<td>-1.45</td>
<td>0</td>
<td>1.4</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

**1.4.5 The Dynamic Model**

The model contained in (1.38)–(1.40) is static and represents the long-run equilibria of the system. Dynamic adjustment to the equilibria is captured by lagged differences in each equation. In tourism demand equations, these are due to the delayed response of travel demand to income and price changes. In the
supply equation, it reflects the gradual adjustment in hotel room prices to changes in demand and supply factors.

Based on the long-run cointegrating vectors, we have:

\[ vus_{hi_t} = 5 \cdot nir_{us_t} - 1.2 \cdot (prm_{hi_t} - cpi_{us_t}) - 0.024 \cdot t + ECM_{vus}; \]
\[ vjp_{hi_t} = 5.2 \cdot nir_{jp_t} - 0.23 \cdot prm_{hi_t} - 3.42 \cdot trms_{hi_t} - 0.31 \cdot p_{jp_t} + ECM_{vjp}; \]
\[ prm_{hi_t} = 0.15 \cdot (vus_{hi_t} + vjp_{hi_t}) + 0.86 \cdot ocup_{hi_t} + 1.45 \cdot trms_{hi_t} - 1.4 \cdot cpi_{us_t} + 0.018 \cdot t + ECM_{prm}; \]

where \( ECM_{vus} \), \( ECM_{vjp} \), and \( ECM_{prm} \) are the three equilibrium errors, with which the following VECM is estimated:

\[ \Delta y_t = c_0 + \omega \Delta x_t + \sum_{i=1}^{4} \Gamma_i \Delta x_{t-1} + \alpha_{1y} ECM_{vus} + \alpha_{2y} ECM_{vjp} + \alpha_{3y} ECM_{prm} + u_t \]  

(1.41)

and \( \alpha_{1y} \), \( \alpha_{2y} \), and \( \alpha_{3y} \) are 3-dimensional vectors of loading parameters. At this stage, dynamics are simplified by dropping statistically insignificant terms. This involves excluding first differenced terms that have \( t \)-statistics less than 2, starting from the smallest. The error correction terms are eliminated by the same criterion. A total of 134 zero restrictions are applied. The \( \chi^2 \) statistic is 166.7 with a \( p \)-value equal to 2.91%. I do not reject these exclusion restrictions at the 1% level. The estimated loading parameters and corresponding diagnostic test statistics are shown in table 1.7.

Not withstanding some of the counter intuitive cointegrating coefficients, the estimated system appears to be an adequate model for Hawaii tourism activity. All equations perform reasonably well, explaining 54%, 67%, 54%, 61% and 70% of the variation in \( \Delta vus_{hi} \), \( \Delta vjp_{hi} \), \( \Delta prm_{hi} \), \( \Delta ocup_{hi} \), and \( \Delta trms_{hi} \) respectively. All equations pass all diagnostic tests at the 1% significance level. The existence of long-run equilibrium error terms (ECMs) in each equation allows for temporary
Table 1.7: Estimates of the Error Correction Coefficients and Diagnostic Statistics

<table>
<thead>
<tr>
<th>Equation</th>
<th>$\alpha_1y$</th>
<th>$\alpha_2y$</th>
<th>$\alpha_3y$</th>
<th>$R^2$</th>
<th>AR(1-5)</th>
<th>$X_N^2$</th>
<th>ARCH</th>
<th>$X_i^2$</th>
<th>Reset</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta vvs_hi$</td>
<td>-0.11</td>
<td>-</td>
<td>-</td>
<td>0.54</td>
<td>0.89</td>
<td>2.13</td>
<td>0.26</td>
<td>0.89</td>
<td>0.21</td>
</tr>
<tr>
<td></td>
<td>(-3.20)</td>
<td></td>
<td></td>
<td></td>
<td>[0.50]</td>
<td>[0.34]</td>
<td>[0.90]</td>
<td>[0.59]</td>
<td>[0.65]</td>
</tr>
<tr>
<td>$\Delta vjp_hi$</td>
<td>-</td>
<td>-0.17</td>
<td>-0.36</td>
<td>0.67</td>
<td>1.56</td>
<td>2.82</td>
<td>1.26</td>
<td>0.33</td>
<td>3.46</td>
</tr>
<tr>
<td></td>
<td>(-2.48)</td>
<td>(-2.90)</td>
<td></td>
<td></td>
<td>[0.19]</td>
<td>[0.24]</td>
<td>[0.30]</td>
<td>[0.99]</td>
<td>[0.07]</td>
</tr>
<tr>
<td>$\Delta prm_hi$</td>
<td>-0.07</td>
<td>-0.12</td>
<td>-0.39</td>
<td>0.54</td>
<td>1.07</td>
<td>0.22</td>
<td>0.66</td>
<td>0.74</td>
<td>0.37</td>
</tr>
<tr>
<td></td>
<td>(-4.42)</td>
<td>(-3.73)</td>
<td>(-7.02)</td>
<td></td>
<td>[0.39]</td>
<td>[0.89]</td>
<td>[0.62]</td>
<td>[0.75]</td>
<td>[0.54]</td>
</tr>
<tr>
<td>$\Delta ocup_hi$</td>
<td>-0.01</td>
<td>-</td>
<td>0.12</td>
<td>0.61</td>
<td>1.69</td>
<td>0.16</td>
<td>1.03</td>
<td>0.87</td>
<td>4.76</td>
</tr>
<tr>
<td></td>
<td>(-2.23)</td>
<td>(2.18)</td>
<td></td>
<td></td>
<td>[0.15]</td>
<td>[0.92]</td>
<td>[0.40]</td>
<td>[0.61]</td>
<td>[0.03]</td>
</tr>
<tr>
<td>$\Delta trms_hi$</td>
<td>-0.02</td>
<td>-0.07</td>
<td>-</td>
<td>0.70</td>
<td>1.26</td>
<td>1.01</td>
<td>0.55</td>
<td>0.78</td>
<td>1.06</td>
</tr>
<tr>
<td></td>
<td>(-2.11)</td>
<td>(-4.66)</td>
<td></td>
<td></td>
<td>[0.30]</td>
<td>[0.60]</td>
<td>[0.70]</td>
<td>[0.73]</td>
<td>[0.31]</td>
</tr>
</tbody>
</table>

Note: Column 1 lists the dependent variable of individual equations in the system; Column 2 to 4 gives the regression coefficient and the corresponding Student t-statistic for the three identified cointegrating vectors; Column 5 presents the coefficient of determination $R^2$; Column 6 lists the test statistics for autocorrelated residuals, performed through the auxiliary regression of the residuals on the original variables and lagged residuals. Column 7 is the $X^2$ normality test on regression residuals. Column 8 is the autoregressive conditional heteroscedasticity (ARCH) test following Engle (1982). It is done by regressing the squared residuals on a constant and lagged squared residuals and testing the significance of the lagged squared residuals. Column 9 is another heteroscedasticity test based on White (1980), which involves an auxiliary regression of the squared residuals on a constant, the original regressors and the original regressors squared. Column 10 is the functional form mis-specification test. It amounts to adding powers (2,3,4) of the fitted values to the original regression. The null is no functional mis-specification, which would be rejected if the test statistic is too high. Figures in parenthesis (.) are the Student t-statistics corresponding to the loading parameters whereas those in brackets [.] are p-values for individual tests.
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 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 ECMs enter the five equations differently. \( \Delta vus_{hi} \) equation contains only \( ECM_{vus} \) with a loading parameter of -0.11, so 11% of the equilibrium error is corrected each quarter. \( \Delta vjp_{hi} \) equation contains both \( ECM_{vjp} \) and \( ECM_{prm} \) with the coefficient on the latter twice of that on the former. This implies that dis-equilibrium in hotel room price has a larger dampening effects on visitors from Japan. All three ECMs enter \( \Delta prm_{hi} \) equation significantly. The estimated parameter on \( ECM_{prm} \) is relatively large, reflecting the high incentive to adjust markup in maintaining occupancy. The hotel occupancy equation contains both \( ECM_{vus} \) and \( ECM_{prm} \). The presence of \( ECM_{vus} \) signifies the importance of U.S. visitor arrivals in determining hotel occupancy due to its size.\(^1\) The last equation, hotel room stock, responds to both \( ECM_{vus} \) and \( ECM_{vjp} \) with a much higher coefficient on Japanese tourists. The dynamic model is picked over sample period 1980Q1-1997Q4, leaving 14 observations for ex post forecasts. Figure 1.5 plots \( \Delta vus_{hi} \), \( \Delta vjp_{hi} \), \( \Delta prm_{hi} \), \( \Delta ocup_{hi} \), \( \Delta trms_{hi} \), the corresponding dynamic ex post forecasts, together with the 95% confidence error bands.

### 1.5 Forecast Encompassing

This section evaluates the forecasting capability of the newly identified Hawaii tourism model. In order to provide some benchmarks, the evaluation is done in comparison to two rival models. The first is a simple no-change model in which

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\(^1\)To understand the ECMs in the occupancy equation, recall that they enter in first lags. So if in the previous quarter U.S. arrivals are higher than prescribed by U.S. real income and relative cost of a Hawaii vacation, U.S. arrivals this period tend to go down, resulting in a downward pressure on occupancy rate. Similarly, if hotel room rate in the last period is higher than warranted by the equilibrium relation, it has a tendency to decrease this quarter, leading to higher occupancy rate.
Figure 1.5: Dynamic Forecasts With Error Bands
the best forecast for next quarter and all future quarters is the observed value this quarter. The second model is the tourism forecasting model maintained by the University of Hawaii Economic Research Organization (UHERO). The UHERO tourism model is a structural multi-equation forecasting model with single equation estimation. The goal here is to test whether any forecast accuracy is gained by fully accounting for the structural relationships using system estimation.

The criterion used is forecast encompassing. Forecast encompassing concerns whether $h$-step ahead forecasts from one model can explain the forecast errors made by another. The test was originally proposed by Chong and Hendry (1986) as a feasible way to evaluate large-scale econometric models. In the literature, forecasting encompassing is closely related to forecast combination and forecast "conditional efficiency" (see Bates and Granger, 1969 for the former and Nelson, 1972 and Granger and Newbold, 1973 for the latter).

The basic concept in forecast encompassing is straight-forward. Let $\hat{y}_j$ denote the $h$-step ahead forecast of $y_j$ from model $M_1$, and $\bar{y}_j$ a corresponding forecast from model $M_2$. The combination forecast is given by,

$$\bar{y}_j = (1 - \alpha)\hat{y}_j + \alpha\bar{y}_j. \quad (1.42)$$

If the estimate of $\alpha$ is neither zero nor unity, both forecasts contain valuable information in forecasting $y_j$, but neither is sufficient. Put alternatively, if the forecast error from $M_1$ is given by $y_j - \hat{y}_j = \hat{u}_j$ and that from $M_2$ by $y_j - \bar{y}_j = \bar{u}_j$, from equation (1.42),

$$y_j - \bar{y}_j = y_j - \hat{y}_j + \alpha(\hat{y}_j - \bar{y}_j) = \hat{u}_j - \alpha(\hat{u}_j - \bar{u}_j) = \bar{u}_j. \quad (1.43)$$

If $\alpha \neq 0$, then the difference between the forecast errors of the two models can help explain the forecast errors of $M_1$, so that $M_1$ could be improved by incorporating some of the features of $M_2$.

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12Details of the model are available from the author at request.
From equation (1.43), we have,

\[ \hat{u}_j = \alpha(\hat{u}_j - \hat{u}_j) + \bar{u}_j. \]  

(1.44)

A forecast encompassing test is implemented by regressing \( \hat{u}_j \) on \( \hat{u}_j - \hat{u}_j \) and using a t-test of \( H_0 : \alpha = 0 \). If the null is rejected, then model \( M_1 \) does not forecast encompass model \( M_2 \).

When the series is integrated, i.e., \( y_j \sim I(1) \), as long as the two models are sufficiently well specified such that \( y_j - \hat{y}_j \sim I(0) \) and \( y_j - \bar{y}_j \sim I(0) \), then:

\[ (\hat{u}_j - \hat{u}_j) \sim I(0), \]

(1.45)

Both the regressand and regressor are \( I(0) \) in (1.44) under the null and the alternative.

Rolling samples are used in the exercise except for the \textit{UHERO-tourmod} which is estimated over full sample. In this sense, \textit{UHERO-tourmod} forecasts are in-sample dynamic forecasts and are expected to perform significantly better.\footnote{For fair comparison, it is ideal to apply rolling sample to all models involved. However, the \textit{UHERO-tourmod} is a multi-equation system containing hundreds of equations. It is difficult to re-estimate the system.} \textit{Coint-tourmod} is estimated over sample period 1980Q1–1997Q4, leaving data over period 1998Q1–2001Q2 for \textit{ex post} forecasts. To execute, the estimation ending period is set to 1997Q4 initially and one- through eight-step ahead dynamic forecasts are generated for 1998Q1–1999Q4. The sample end is then moved one-step ahead to 1998Q1 and another set of one- through eight-step ahead dynamic forecasts generated for 1998Q2-2000Q1. We continue the process till the sample end is reached. We obtain 14 one-step, 13 two-step, 11 four-step and 7 eight-step ahead dynamic forecasts. Forecast encompassing is then performed on forecast errors of \( \Delta vus_h, \Delta vjp_h, \Delta prm_h, \Delta ocup_h, \Delta trms_h \) in pairs: \textit{Coint-tourmod} against \textit{UHERO-tourmod}, \textit{Coint-tourmod} against \textit{RW-tourmod}, and \textit{UHERO-tourmod} against \textit{RW-tourmod}. For instance, to test if \textit{Coint-tourmod} forecast encompasses \textit{RW-tourmod}, I regress forecast errors from the \textit{Coint-tourmod} onto
the difference between the forecast errors from Coint-tourmod and those from RW-tourmod and test whether coefficients on the error differences are zeros. The test statistic follows a $t$-distribution under the null.

All encompassing test results are listed in tables 1.8 through 1.12. To read the table, each model listed by row is the control model and every model listed by column is a rival model. For instance, row one in table 1.8 presents encompassing test results of one-quarter ahead forecasts for $\Delta \text{vus}_\text{hi}$ when Coint-tourmod is the control model and the rival models are UHERO-tourmod and RW-tourmod respectively. The diagonal line shows not applicable (n.a.) as a model can not forecast encompass itself.

From tables 1.8 to 1.12, we cannot reject the null hypothesis that Coint-tourmod forecast encompasses RW-tourmod for all endogenous variables at all forecast horizons except $\Delta \text{ocup}_\text{hi}$ at four-quarter ahead and $\Delta \text{trms}_\text{hi}$. For $\Delta \text{trms}_\text{hi}$, the null hypothesis of Coint-tourmod forecast encompassing RW-tourmod is rejected at 1% significance at all forecast horizons. The converse, RW-tourmod forecast encompassing Coint-tourmod for $\Delta \text{trms}_\text{hi}$ is not rejected at any forecast horizon. The evidence indicates that a simple no-change model in first differences offers a better specification for hotel room stock. This is not surprising given the fact that modelled Hawaii hotel room inventory stays relatively flat for the forecast period, while the room stock equation is driven by arrivals etc. When comparing Coint-tourmod to UHERO-tourmod, we reject the null hypothesis that Coint-tourmod forecast encompasses UHERO-tourmod except for $\Delta \text{vjp}_\text{hi}$ and $\Delta \text{prm}_\text{hi}$ at eight-quarter ahead, and $\Delta \text{ocup}_\text{hi}$ at two-, four-, and eight-quarter ahead. The converse, UHERO-tourmod forecast encompasses Coint-tourmod, is not rejected for any of the variables at any horizon. This may be explained by the fact that UHERO-tourmod is estimated using full sample while Coint-tourmod is estimated using only sample 1980Q1–1997Q4. Overall, the newly identified Coint-tourmod performs relatively well against UHERO-tourmod and RW-tourmod, especially at longer forecast horizons.

---

The room stock measure does not capture all of the year-to-year variation due to movements of condominiums, apartments, time-shares in and out of the lodging supply.
Table 1.8: Forecast Encompassing Test – $\Delta vus.hi$

<table>
<thead>
<tr>
<th>Model</th>
<th>Coint-tourmod</th>
<th>UHERO-tourmod</th>
<th>RW-tourmod</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>One-quarter ahead</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Coint-tourmod</td>
<td>n.a.</td>
<td>41.7</td>
<td>0.03</td>
</tr>
<tr>
<td></td>
<td>–</td>
<td>[0.00]</td>
<td>[0.86]</td>
</tr>
<tr>
<td>UHERO-tourmod</td>
<td>0.43</td>
<td>n.a.</td>
<td>1.5</td>
</tr>
<tr>
<td></td>
<td>[0.52]</td>
<td>–</td>
<td>[0.24]</td>
</tr>
<tr>
<td>RW-tourmod</td>
<td>10.8</td>
<td>94.9</td>
<td>n.a.</td>
</tr>
<tr>
<td></td>
<td>[0.00]</td>
<td>[0.00]</td>
<td>–</td>
</tr>
<tr>
<td><strong>Two-quarter ahead</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Coint-tourmod</td>
<td>n.a.</td>
<td>11.6</td>
<td>7.12</td>
</tr>
<tr>
<td></td>
<td>–</td>
<td>[0.005]</td>
<td>[0.02]</td>
</tr>
<tr>
<td>UHERO-tourmod</td>
<td>0.18</td>
<td>n.a.</td>
<td>0.89</td>
</tr>
<tr>
<td></td>
<td>[0.68]</td>
<td>–</td>
<td>[0.37]</td>
</tr>
<tr>
<td>RW-tourmod</td>
<td>9.39</td>
<td>16.0</td>
<td>n.a.</td>
</tr>
<tr>
<td></td>
<td>[0.01]</td>
<td>[0.00]</td>
<td>–</td>
</tr>
<tr>
<td><strong>Four-quarter ahead</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Coint-tourmod</td>
<td>n.a.</td>
<td>25.3</td>
<td>1.06</td>
</tr>
<tr>
<td></td>
<td>–</td>
<td>[0.00]</td>
<td>[0.33]</td>
</tr>
<tr>
<td>UHERO-tourmod</td>
<td>0.03</td>
<td>n.a.</td>
<td>3.64</td>
</tr>
<tr>
<td></td>
<td>[0.86]</td>
<td>–</td>
<td>[0.09]</td>
</tr>
<tr>
<td>RW-tourmod</td>
<td>17.25</td>
<td>108.1</td>
<td>n.a.</td>
</tr>
<tr>
<td></td>
<td>[0.00]</td>
<td>[0.00]</td>
<td>–</td>
</tr>
<tr>
<td><strong>Eight-quarter ahead</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Coint-tourmod</td>
<td>n.a.</td>
<td>31.3</td>
<td>7.96</td>
</tr>
<tr>
<td></td>
<td>–</td>
<td>[0.001]</td>
<td>[0.03]</td>
</tr>
<tr>
<td>UHERO-tourmod</td>
<td>0.00009</td>
<td>n.a.</td>
<td>2.46</td>
</tr>
<tr>
<td></td>
<td>[0.99]</td>
<td>–</td>
<td>[0.17]</td>
</tr>
<tr>
<td>RW-tourmod</td>
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<td>22.04</td>
<td>n.a.</td>
</tr>
<tr>
<td></td>
<td>[0.00]</td>
<td>[0.003]</td>
<td>–</td>
</tr>
</tbody>
</table>

Note: Column 1 lists the control model; Column 2 to 4 give the rival models and the corresponding t-statistic on forecast encompassing at different horizons. Numbers in brackets [.] are corresponding p-values. All bold inputs indicate significance at 1% significance level.
Table 1.9: Forecast Encompassing Test – $\Delta vjp_{hi}$

<table>
<thead>
<tr>
<th>Model</th>
<th>Coint-tourmod</th>
<th>UHERO-tourmod</th>
<th>RW-tourmod</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>One-step ahead</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Coint-tourmod</td>
<td>n.a.</td>
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<td>0.01</td>
</tr>
<tr>
<td></td>
<td></td>
<td>[0.00]</td>
<td>[0.91]</td>
</tr>
<tr>
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<td>n.a.</td>
<td>1.27</td>
</tr>
<tr>
<td></td>
<td>[0.70]</td>
<td>–</td>
<td>[0.28]</td>
</tr>
<tr>
<td>RW-tourmod</td>
<td><strong>14.1</strong></td>
<td><strong>79.8</strong></td>
<td>n.a.</td>
</tr>
<tr>
<td></td>
<td>[0.00]</td>
<td>[0.00]</td>
<td>–</td>
</tr>
<tr>
<td></td>
<td>Two-quarter ahead</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Coint-tourmod</td>
<td>n.a.</td>
<td><strong>15.7</strong></td>
<td>1.19</td>
</tr>
<tr>
<td></td>
<td></td>
<td>[0.00]</td>
<td>[0.30]</td>
</tr>
<tr>
<td>UHERO-tourmod</td>
<td>0.0005</td>
<td>n.a.</td>
<td>0.007</td>
</tr>
<tr>
<td></td>
<td>[0.98]</td>
<td>–</td>
<td>[0.94]</td>
</tr>
<tr>
<td>RW-tourmod</td>
<td>6.34</td>
<td><strong>26.6</strong></td>
<td>n.a.</td>
</tr>
<tr>
<td></td>
<td>[0.03]</td>
<td>[0.00]</td>
<td>–</td>
</tr>
<tr>
<td></td>
<td>Four-quarter ahead</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Coint-tourmod</td>
<td>n.a.</td>
<td><strong>21.6</strong></td>
<td>2.8</td>
</tr>
<tr>
<td></td>
<td></td>
<td>[0.00]</td>
<td>[0.13]</td>
</tr>
<tr>
<td>UHERO-tourmod</td>
<td>0.41</td>
<td>n.a.</td>
<td>0.18</td>
</tr>
<tr>
<td></td>
<td>[0.54]</td>
<td>–</td>
<td>[0.68]</td>
</tr>
<tr>
<td>RW-tourmod</td>
<td>2.4</td>
<td><strong>20.01</strong></td>
<td>n.a.</td>
</tr>
<tr>
<td></td>
<td>[0.15]</td>
<td>[0.00]</td>
<td>–</td>
</tr>
<tr>
<td></td>
<td>Eight-quarter ahead</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Coint-tourmod</td>
<td>n.a.</td>
<td>5.81</td>
<td>1.17</td>
</tr>
<tr>
<td></td>
<td></td>
<td>[0.05]</td>
<td>[0.32]</td>
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<td>0.00002</td>
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<tr>
<td></td>
<td>[0.67]</td>
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<td>[0.99]</td>
</tr>
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<td>RW-tourmod</td>
<td><strong>15.85</strong></td>
<td><strong>14.92</strong></td>
<td>n.a.</td>
</tr>
<tr>
<td></td>
<td>[0.00]</td>
<td>[0.00]</td>
<td>–</td>
</tr>
</tbody>
</table>

Note: Column 1 lists the control model; Column 2 to 4 give the rival models and the corresponding t-statistic on forecast encompassing at different horizons. Numbers in brackets [.] are corresponding p-values. All bold inputs indicate significance at 1% significance level.
<table>
<thead>
<tr>
<th>Model</th>
<th>Coint-tourmod</th>
<th>UHERO-tourmod</th>
<th>RW-tourmod</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>One-quarter ahead</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Coint-tourmod</td>
<td>n.a.</td>
<td>14.9</td>
<td>5.54</td>
</tr>
<tr>
<td></td>
<td></td>
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<td>[0.03]</td>
</tr>
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<td>n.a.</td>
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</tr>
<tr>
<td></td>
<td>[0.53]</td>
<td></td>
<td>[0.88]</td>
</tr>
<tr>
<td>RW-tourmod</td>
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<td>27.6</td>
<td>n.a.</td>
</tr>
<tr>
<td></td>
<td>[0.00]</td>
<td>[0.00]</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Two-quarter ahead</td>
<td></td>
<td></td>
</tr>
<tr>
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<td>[0.007]</td>
<td>[0.00]</td>
<td></td>
</tr>
</tbody>
</table>

Note: Column 1 lists the control model; Column 2 to 4 give the rival models and the corresponding t-statistic on forecast encompassing at different horizons. Numbers in brackets [.] are corresponding p-values. All bold inputs indicate significance at 1% significance level.
Table 1.11: Forecast Encompassing Test – $\Delta ocup_{hi}$

<table>
<thead>
<tr>
<th>Model</th>
<th>Coint-tourmod</th>
<th>UHERO-tourmod</th>
<th>RW-tourmod</th>
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</table>

Note: Column 1 lists the control model; Column 2 to 4 give the rival models and the corresponding t-statistic on forecast encompassing at different horizons. Numbers in brackets [.] are corresponding p-values. All bold inputs indicate significance at 1% significance level.
<table>
<thead>
<tr>
<th>Model</th>
<th>Coint-tourmod</th>
<th>UHERO-tourmod</th>
<th>RW-tourmod</th>
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<tbody>
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Note: Column 1 lists the control model; Column 2 to 4 give the rival models and the corresponding t-statistic on forecast encompassing at different horizons. Numbers in brackets [.] are corresponding p-values. All bold inputs indicate significance at 1% significance level.
1.6 Concluding Remarks

The paper presents the first attempt in the literature to estimate a complete tourism model using the state of art cointegrating analysis tools. Unlike previous work that are exclusively demand oriented, both demand and supply factors are considered in the framework. For tourism activities in Hawaii, the paper identifies one demand relation each for the U.S. and Japanese visitors and an inverse supply curve depicting average hotel room prices. By formally incorporating the supply side, the Hawaii tourism model may be less liable to regression biases caused by demand and supply interactions.

The paper follows the latest cointegration methodologies in identifying long-run cointegrating vectors and reducing the system to the most parsimonious representation. Instead of relying on pure statistical identification method of Johansen, it applies the theory-guided approach advocated by Pesaran and Smith (1998) and Pesaran and Shin (2001). Compared to the Johansen procedure, the theory-guided approach is easy to comprehend and identifies economically meaningful cointegrating vectors. For the Hawaii tourism model, over-identifying restrictions are imposed on each of the three long-run cointegrating vectors.

The paper also follows Hall, Henry, and Greenslade (2002) method in system reduction. Rather than estimating a full model, the paper tests and imposes weak exogeneity assumptions at the earliest stage in the model reduction process. As a result, the number of parameters estimated is greatly reduced, saving degrees of freedom and improving the efficiency of estimated coefficients. When testing weak exogeneity assumptions, the paper employs two methods: 1) the standard Johansen (1991) condition of setting a whole row in the loading matrix $\alpha$ to zero; 2) the Harbo, Johansen, Nielsen, and Rahbek (1998) method of assuming weak exogeneity and testing the significance of identified cointegrating vectors in the marginal model. The Hawaii tourism model demonstrates that when exogenous variables are cointegrated among themselves, the Harbo et. al. method is more effective in establishing weak exogeneity.

Not every aspect of the identified model is a success, however. The estimated
income elasticities for both the U.S. and Japanese visitors are a bit on the high side. Coefficients on some other variables have signs contrary to expected. These deficiencies demonstrate the difficulties faced by empirical modelers when estimating a big complete system with limited macro data set. It is therefore important to design the system in the most efficient way at the outset.

The methods laid out in this paper are applicable to supply and demand analysis in any economic field. From a macro perspective, it can be applied to money demand and supply studies to analyze the central bank behavior. From a micro perspective, application may extend to personal consumption decision making if good quality data exists. It would be interesting to see how system cointegration analysis finds its application in a bigger arena.
Appendix. Data Illustration

Measures of Hawaii Tourism Activities

Beginning in 2000, the State of Hawaii Department of Business Economic Development & Tourism (DBEDT) changed its methodology for compiling tourism statistics. Instead of the previous breakdown into westbound and eastbound directions of travel, the new methodology reports domestic and international visitor counts. According to Hawaii’s Economy (issue 2-01), these two methodologies differ in the treatment of Canadian visitor arrivals. In the old methodology, visitors from Canadian ports were counted as westbound visitors while in the new methodology they are part of international arrivals. Both methodologies use breakdowns by port of departure, not by the residency of visitors.

However, complete time series for Hawaii tourism activity is needed for modeling purposes. Three approaches are available in obtaining the series:

1. For the post 2000 period, convert the new domestic and international data to the old westbound and eastbound measures;

2. For the pre 2000 period, convert the old westbound and eastbound series to the new domestic and international measures;

3. Reorganize and construct full data series according to visitor nationality or residency.

The first two approaches involve the following conversion formula:

\[ viseb_{hi} = visit_{hi} - visit_{hi}^{can}; \]

\[ viswb_{hi} = visdm_{hi} + visit_{hi}^{can}. \]

where \( viseb_{hi} \) is Hawaii eastbound visitor arrivals and \( viswb_{hi} \) is westbound arrivals; \( visit_{hi} \) is international visitor counts and \( visdm_{hi} \) is domestic visitor counts; \( visit_{hi}^{can} \) is international arrivals from Canadian ports.

DBEDT reports monthly country breakdowns of domestic and international visitor counts for the post 1989 period, including an international Canadian
category. Under the assumption that this number is equal to total arrivals from Canadian ports, the conversion from domestic and international to westbound and eastbound for the post 2000 period is feasible. The converse, from westbound and eastbound to domestic and international, is almost impossible because historical Canadian arrivals from international ports are simply not available.

Though feasible, the first approach should not be adopted because a model built on old measures has limited empirical values. Considering that U.S. and Japanese arrivals account for around 85 percent of the market over the past decade, the third approach—constructing U.S. and Japanese visitor counts series—seems most appealing.

Monthly U.S. and Japanese visitor statistics for the post 1989 period are compiled and reported by DBEDT. For the pre 1989 period, arrivals by country data exists only on an annual basis from the State of Hawaii Data Book. To construct a higher frequency series, annual numbers are interpolated using the seasonal patterns of corresponding monthly series. In particular, the westbound arrival pattern is used to interpolate U.S. annual numbers and the eastbound pattern is applied to Japanese annual counts. The monthly westbound arrival series is obtained from the Monthly Research Report of Hawaii Visitor & Convention Bureau (HVCB). Eastbound series comes from the Annual Research Report of the HVCB. The constructed U.S. and Japanese monthly arrival series are then aggregated to quarterly and seasonally adjusted.
ESSAY 2

Forecasting Hawaii Construction Activity in a Cointegrating Bayesian VAR Framework

2.1 Introduction

Regional construction activity receives a great deal of attention because it represents a fundamental and highly variable component of state and local economic activity. In many regions of the country, construction forecasts are closely watched because of their close connections with market growth and general business conditions. Commercial banks and other credit agencies monitor residential and commercial building trends to assess future business potential. Retail furnishings and home appliances stores subscribe to regional housing starts projections to ensure proper staffing and inventory levels. In the public sector, residential building trends have been found to directly affect regional sales tax collections (Fullerton and West, 1998; Fullerton, 2001). Public utilities also use construction forecasts to plan for additional pipelines and electricity distribution substations.

Despite this importance, the forecasting literature has few examples of models specific to regional construction activity. Each state of the union maintains its own econometric model for policy analysis and economic planning. Typically such models contain equations focusing on regional investment activities—often
represented by residential and non-residential construction. Nevertheless, these models are macroeconomic income and product accounts theory driven and requires corresponding data which are not readily available at subnational levels from standard sources (such as Bureau of Economic Analysis (BEA), Bureau of Labor Statistics (BLS), etc.). Forecasts from these models are generally less than satisfactory (see, for instance, Fullerton and West, 1998; Fullerton, Luevano, and West, 2000; Fullerton,Laaksonen and West, 2001).

In the late 1970s, a less theory dependent technique—vector autoregression (VAR)—was first used in the regional modeling literature (Anderson, 1979). Compared to structural models, the VAR methodology is based more on regularities of the data than on economic theory. In an unrestricted VAR, economic theory is used primarily to select variables and lag lengths. Variables chosen are logically related and portray historical patterns. However, the very specification of VAR yields it vulnerable to multicollinearity and overparameterization problems.

One way to deal with overparameterization is the Bayesian VAR (BVAR) technique, developed by Litterman (1980, 1986) and summarized in Todd (1984). Instead of eliminating insignificant variables and lags entirely, the method preserves all variables at all preselected lag lengths. Normal distributions are assumed for parameters of interest such that variables and lags of less importance have smaller prior standard deviations around prior means of zeros. Models with the so-called Minnesota prior have demonstrated promising forecasting capabilities (McNees, 1986; Litterman, 1986). In recent years, the Minnesota prior has been extended to both a symmetric treatment of the dependent and independent variables—the Normal-Wishart prior (Kadiyala and Karlsson, 1993, 1997), and linear combinations of coefficients—the sums of coefficients prior (Doan, Litterman, and Sims, 1984) and the dummy initial observation prior (Sims, 1993).

The BVAR technique has been gradually accepted as a low-cost alternative to large-scale structural systems at both the national and regional levels (see Todd, 1984; Amirizadeh, 1985; Litterman, 1986; Sims, 1993; Chin, 1999 for the former; and Cargill and Morus, 1988; Crone and McLaughlin, 1999; Dua and Ray, 1995; Patridge and Rickman, 1998; Whiteman, 1997; Puri and Soydemir, 2000; and
Rickman, 2000 for the latter). For the construction industry, Dua and other researchers construct home sales forecast models for the State of Connecticut and the entire country (Dua and Smyth, 1995; Dua and Miller, 1996; Dua, Miller, and Smyth, 1999). They compare different BVAR specifications and find that models with building permits as leading indicators produce the most accurate forecasts.

This paper constructs a high-frequency construction forecast model for Hawaii, incorporating the latest sums of coefficients and dummy initial observation priors. It makes a contribution to the literature in two ways: First, the paper introduces BVAR models with linear combination priors to regional construction forecasts. Robertson and Tallman (1999) estimate a six-variable U.S. macroeconomic BVAR model and show that forecasts from specifications with these linear combination priors are superior to those from a similar specification but without the priors. Second, the paper systematically compares the forecasting performance of a BVAR with linear combination priors with other VAR and BVAR specifications. In particular, the different specifications include an unrestricted VAR in levels, an unrestricted VAR in first differences, and a BVAR with a pure Minnesota prior.

The organization of the essay is as the following. Section 2.2 discusses the conceptual issues of BVAR methods using both the Minnesota prior and other modified priors. Section 2.3 reviews the existing literature on construction/housing modeling and forecasting. Section 2.4 lists variables used in the Hawaii construction model and presents the estimation results. Section 2.5 evaluates the forecasting performance of the BVAR construction model relative to other rival models. Section 2.6 concludes.

### 2.2 The Bayesian VAR Methodology and Priors

Consider the following VAR(\(k\)) model in an \(m \times 1\) vector of variables \(z_t\),

\[
  z_t = \Phi_1 z_{t-1} + \cdots + \Phi_k z_{t-k} + c + \epsilon_t, \quad t = 1, 2, \ldots, T, \tag{2.1}
\]

where \(k\), the order of the VAR, is assumed to be known a priori; \(c\) is an \(m \times 1\)
vector of unknown constants; \( \Phi_l, l = 1, 2, \ldots, k \), are \( m \times m \) matrices of unknown parameters; \( \epsilon_t \) is an \( m \times 1 \) vector of disturbances that is i.i.d. \((0, \Omega)\) and the initial values, \( z_0, z_{-1}, \ldots, z_{-k+1} \) are taken as given.

The unrestricted VAR system in (2.1) suffers from severe lack of degrees of freedom. Each equation of the VAR involves estimating \( mk \) 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. Forecasts based on unrestricted Ordinary Least Squares (OLS) estimation of (2.1) for finite samples is not well determined. To solve the problem, Hoehn (1984) and Hoehn, Gruben, and Fomby (1984) offer statistical tests to eliminate insignificant variables and lags to reduce the amount of overparameterization and therefore improve forecast accuracy, but their tests are time consuming. A more straight-forward solution is found in Litterman (1980) which makes use of Theil’s (1971) mixed regression technique and suggests a Bayesian method to estimate the coefficients for economic series with trends or persistent local levels. Instead of treating the underlying parameters as fixed values to be discovered by regression tools, Litterman treats coefficients as random quantities around prior mean values, where the tightness of the distribution around prior mean is determined via a set of hyperparameters. The main technical issues thus involve the specification of prior distribution and the determination of the form of estimators.

### 2.2.1 The Minnesota Prior

The “Minnesota Prior” owes its name to its development at the Federal Reserve Bank of Minneapolis and the University of Minnesota (Litterman, 1980). Under the prior, individual elements of each lag coefficient matrix \( \Phi_l \) in (2.1) are independently and normally distributed random variables with the mean of the coefficient matrix on the first lag, \( \Phi_1 \), equal to an identity matrix and the mean of the coefficient matrices on other lags, \( \Phi_l, l = 2, 3, \ldots, k \), equal to zero.\(^1\) If

\(^1\)This is equivalent as saying that the prior mean for the first lag of the dependent variable is one and the prior mean for everything else is zero.
these restrictions were exact, each variable in (3.1) would follow a random walk process, possibly with nonzero drift. In the BVAR setting, however, the random walk assumption does not have to be imposed exactly, but is specified as inexact prior with the standard deviation, $S(i,j,l)$, of the $ij$-th element in the $l$-th lag coefficient matrix $\Phi_l$ given by,

$$S(i,j,l) = \begin{cases} 
\lambda_1/l\lambda_3 & \text{if } i = j, \\
\sigma_i\lambda_2/\sigma_jl\lambda_3 & \text{if } i \neq j.
\end{cases}$$  \hfill (2.2)

In equation (2.2), $\lambda_1$ is the overall tightness parameter. It is the prior standard deviation of the $ii$-th element of $\Phi_1$ and controls how closely the random walk prior is imposed. As $\lambda_1$ approaches zero, the diagonal elements of $\Phi_1$ approach one and all other coefficients shrink to zero, i.e., a stronger random walk assumption. Because own lags tend to be more important in explaining the dependent variable than lags of other variables, coefficients on lags of other variables are assigned a relatively smaller variance around the prior mean of zero. This relative tightness is controlled by choosing a value for $\lambda_2$ that is between zero and one ($0 < \lambda_2 \leq 1$). A smaller value for $\lambda_2$ has the effect of shrinking the off-diagonal elements of $\Phi_l$ towards zero. If $\lambda_2$ is set to unity, lags of other variables are treated the same as lags of the dependent variable. It is also assumed that the impact of a lagged variable decreases as the lag length increases. This is captured by the parameter $\lambda_3$. As $\lambda_3$ increases, the prior variance of the coefficients on higher order lags shrinks toward zero. If $\lambda_3$ is set to one, the rate of decay is harmonic.\footnote{When monthly data are used to fit a VAR system, a special decay factor is used to approximate a harmonic decay pattern at a quarterly frequency. See Robertson and Tallman (1999).} Finally, the prior standard deviations are scaled by the ratio $(\sigma_i/\sigma_j)$ to account for the different units of measurement for variables in the system. In practice, $\sigma_i$ is usually set to the residual standard deviation of a univariate autoregression on equation $i$. The constant term $c$ in (3.1) has different inexact prior specifications in the literature. The most commonly seen is a prior mean of zero with standard deviation $\sigma_i\lambda_4$. As $\lambda_4$ decreases, the constant shrinks to zero.
To illustrate the Minnesota prior, suppose we have a two-variable system \((m = 2)\) with a lag length of 2 \((k = 2)\). The Minnesota prior has prior means given by,

\[
\tilde{b}_1 = \begin{pmatrix} 0 & 1 & 0 & 0 & 0 \end{pmatrix}', \tag{2.3}
\]

\[
\tilde{b}_2 = \begin{pmatrix} 0 & 0 & 1 & 0 & 0 \end{pmatrix}', \tag{2.4}
\]

and prior variances,

\[
\bar{G}_1 = \begin{pmatrix}
(s_1 \lambda_4)^2 & 0 & 0 & 0 & 0 \\
0 & (\lambda_1)^2 & 0 & 0 & 0 \\
0 & 0 & (s_1 \lambda_1 \lambda_2 / s_2)^2 & 0 & 0 \\
0 & 0 & 0 & (\lambda_1 / 2 \lambda_3)^2 & 0 \\
0 & 0 & 0 & 0 & [s_1 \lambda_1 \lambda_2 / (2 \lambda_3 \sigma_2)]^2
\end{pmatrix}, \tag{2.5}
\]

\[
\bar{G}_2 = \begin{pmatrix}
(s_2 \lambda_4)^2 & 0 & 0 & 0 & 0 \\
0 & (s_2 \lambda_1 \lambda_2 / s_1)^2 & 0 & 0 & 0 \\
0 & 0 & (\lambda_1)^2 & 0 & 0 \\
0 & 0 & 0 & [s_2 \lambda_1 \lambda_2 / (2 \lambda_3 \sigma_1)]^2 & 0 \\
0 & 0 & 0 & 0 & (\lambda_1 / 2 \lambda_3)^2
\end{pmatrix}, \tag{2.6}
\]

where columns of the matrices correspond to \(c\), \(z_{1,t-1}\), \(z_{2,t-1}\), \(z_{1,t-2}\) and \(z_{2,t-2}\) respectively.

To estimate the coefficients, note first that the OLS estimator of coefficients in the \(i\)-th equation of the VAR system in (2.1) is,

\[
\hat{b}_i^{OLS} = (X'X)^{-1}X'z_i, \quad i = 1, 2, \ldots, m, \tag{2.7}
\]

where \(z_i\) is a \(T \times 1\) vector with \(n\)-th element \((z_{i,n})\) and \(X\) is a \(T \times (mk + 1)\) matrix with \(n\)-th row \((1 \quad z_{1,n-1} \quad \cdots \quad z_{m,n-1} \quad z_{1,n-2} \quad \cdots \quad z_{m,n-2} \quad z_{1,n-k} \quad \cdots \quad z_{m,n-k})\). The BVAR estimator is obtained via a Theil's (1971) mixed regression
and the mean of the posterior distribution is given by,

$$\hat{b}_{i}^{BVAR} = (G_{i}^{-1} + \sigma_i^{-2}X'X)^{-1}(G_{i}^{-1}b_i + \sigma_i^{-2}X'z_i). \quad (2.8)$$

In summary, the Bayesian technique allows a model builder to incorporate prior statistical and economic knowledge in a scientific way to specify the best guess for all parameter values. In addition, the model builder specifies confidence in the values of the coefficients. The extent to which data are allowed to revise the modeler’s estimate of a particular coefficient depends on the modeler’s confidence in the guess. If he is highly confident, the historical patterns of the data receive low weight and vice versa. The prior variance or standard deviation of the coefficients measures how confident the modeler is about his prior guess. A small prior variance indicates a high confidence that the estimated coefficients closely match the best guess. A large variance implies that the estimated coefficients might vary significantly from the modeler’s initial guess.

2.2.2 The Normal-Wishart Prior

The BVAR using a Minnesota prior as originally developed by Litterman (1980) is estimated one equation at a time. Litterman (1980) shows that this reduces the computational burden by the square of the number of variables, $km^2$. Nevertheless, single-equation estimation is valid for an unrestricted covariance matrix, $\Omega$, only when the same independent variables appear on the right-hand side of each equation and the prior for each variable has the same form. It is clear that the Minnesota prior violates the second criterion because the parameters controlling the prior variance on other lagged variables ($\lambda_2$) is different from one. In practice, single equation estimation precedes under the assumption that the residual covariance matrix $\Omega$ is close to diagonal. Litterman (1980) acknowledges that “there could be a gain in efficiency by estimating all equations together...the departures from full efficiency will depend on how far from diagonal is the covariance matrix of residuals from different equations and the relative strength of
asymmetric prior information to data evidence".3

Recent work relaxes the assumption of a diagonal covariance matrix by using
the Normal-Wishart prior (Kadiyala and Karlsson, 1993, 1997). Under the Normal­
Wishart prior, the prior distribution of the regression coefficients conditional on
the error covariance matrix Ω is Normal, and the prior distribution of Ω is inverse
Wishart. The coefficient estimator (i.e., the mean of the posterior distribution) is,

$$\hat{B} = (H^{-1} + X'X)^{-1}(H^{-1}B + X'z),$$

(2.9)

where $B$ is the prior mean of the coefficient matrix, and $H$ is the $(mk + 1) \times
(mk + 1)$ diagonal, positive-definite prior covariance matrix. The covariance
matrix estimator is,

$$\hat{\Omega} = T^{-1}(z'z - \hat{B}'(H^{-1} + X'X)\hat{B} + \hat{B}'H^{-1}\hat{B} + \bar{S}),$$

(2.10)

where $\bar{S}$ is a $m \times m$ diagonal scale matrix in the prior inverse-Wishart distribution
for $\Omega$.

We again use a two-variable ($m = 2$), two-lag ($k = 2$) system to illustrate the
Normal-Wishart prior. The prior information is given by,

$$\bar{B} = \begin{pmatrix} 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{pmatrix},$$

(2.11)

$$\bar{S} = \begin{pmatrix} (\sigma_1/\lambda_0)^2 & 0 \\ 0 & (\sigma_2/\lambda_0)^2 \end{pmatrix},$$

(2.12)

\footnote{See Litterman (1980) p. 31-32.}
where parameter $\lambda_0$ governs the overall tightness of the prior on $\Omega$.

It is easy to see the relation between the Minnesota prior and the Normal-Wishart prior. The Normal-Wishart prior involves a Kronecker product of $\mathbf{S}$ and $\mathbf{H}$ which results in an $m(mk+1) \times m(mk+1)$ scale matrix whose elements are exactly the coefficient prior variances under the Minnesota prior with $\lambda_2 = 1$. The restriction applies because the Normal-Wishart prior prohibits lags of the dependent variable from being treated differently from lags of other variables in an equation. Alternatively, the restriction on $\lambda_0$ is the price paid to relax the stringent assumption that residual covariance matrix $\Omega$ is diagonal in the Minnesota prior while retaining the random-walk property.

### 2.2.3 Priors on Linear Combinations of the Coefficients

Another strain of literature seeks to modify the Minnesota prior in the direction of linear combinations of the coefficients in equation (2.1). It introduces nonzero off-diagonal terms into the prior covariance of individual coefficients and is thus more easily implemented from the dual side by mixing a set of dummy observations into the data set. Sims and Zha (1998) show that the Minnesota prior can also be implemented by adding a set of $k - 1$ dummy observations to the matrix used to estimate the $i$-th equation.\(^4\) The only difference is that the “dummy observations” for the Minnesota prior are equation-specific, whereas priors discussed below are

\[^4\text{As is typical in a prime-dual problem, the scale factors on dummy observations are precisely the reciprocal of those on prior covariance matrix.}\]
true, system-wide dummy observations.

**Sums of Coefficients Prior**

In the literature, there are two priors on dummy observations. The first, known as the *sums of coefficients* prior, is introduced in Doan, Litterman, and Sims (1984) and expresses a prior belief that when data contain stochastic trends (unit roots), a VAR in first differences is appropriate. The *sums of coefficients* prior implicitly assumes that coefficients on lags of the dependent variable in each equation sum up to one while coefficients on lags of other variables sum up to zero. Rewrite equation (2.1) in error correction form,

\[
\Delta z_t = -\Pi z_{t-1} + \Gamma_1 \Delta z_{t-1} + \cdots + \Gamma_{k-1} \Delta z_{t-k+1} + c + \epsilon_t,
\]

(2.14)

where \( \Pi = I_m - \sum_{i=1}^k \Phi_i \), \( \Gamma_i = -\sum_{j=i+1}^k \Phi_j, i = 1, \ldots, k - 1 \). Note that when \( \sum_{i=1}^k \Phi_i = I_m \), \( -\Pi z_{t-1} \) drop out of equation (2.14) and the whole system is specified in first differences. In practice, the *sums of coefficients* prior is implemented by adding to the data set \( m \) dummy observations, in which \( X_{t-i} \) is set to zero for \( i = 1, \ldots, k \), except for \( X_{t-i}^j, i = 1, \ldots, k \), which corresponds to the dependent variable and is set to \( z_j^0 \), the mean of the \( k \) presample values for variable \( z_j \). Dummies corresponding to the constant vector are set to zero.

To illustrate the *sums of coefficients* prior, suppose we have a two-variable \((m = 2)\), two-lag \((k = 2)\) system the VAR specification for which is,

\[
\begin{pmatrix} z_{1,t} \\ z_{2,t} \end{pmatrix} = \begin{pmatrix} c_1 \\ c_2 \end{pmatrix} + \begin{pmatrix} z_{1,t-1} \\ z_{2,t-1} \end{pmatrix} \begin{pmatrix} \phi_{1,1}^1 & \phi_{1,1}^2 \\ \phi_{2,1}^1 & \phi_{2,1}^2 \end{pmatrix} + \begin{pmatrix} \phi_{1,2}^1 & \phi_{1,2}^2 \\ \phi_{2,2}^1 & \phi_{2,2}^2 \end{pmatrix} \begin{pmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \end{pmatrix} + \begin{pmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \end{pmatrix} \tag{2.15}
\]

where \( \phi_{j,l}^i \) is the coefficient on the \( l \)-th lag of \( j \)-th variable in the \( i \)-th equation and \( z_{i,t} \) is the \( T \times 1 \) vector of sample observations \((i = 1, 2)\). Imposing the *sums of*
coefficients prior involves stacking to the sample matrix two dummy observations,

\[
\begin{pmatrix}
\bar{z}_1^0 & 0 \\
0 & \bar{z}_2^0
\end{pmatrix},
\]  
(2.16)

for the dependent variables and,

\[
\begin{pmatrix}
0 & \bar{z}_1^0 & 0 & \bar{z}_1^0 & 0 \\
0 & 0 & \bar{z}_2^0 & 0 & \bar{z}_2^0
\end{pmatrix},
\]  
(2.17)

for the independent variables. A weight of \( \lambda_5 \geq 0 \) is attached to these dummy observations. This implies that the following equalities hold,

\[
\begin{pmatrix}
\lambda_5 \bar{z}_1^0 & 0 \\
0 & \lambda_5 \bar{z}_2^0
\end{pmatrix} = \begin{pmatrix}
0 \\
0
\end{pmatrix} (c_1, c_2) + \begin{pmatrix}
\lambda_5 \bar{z}_1^0 & 0 \\
0 & \lambda_5 \bar{z}_2^0
\end{pmatrix} \begin{pmatrix}
\phi_{1,1}^1 & \phi_{1,1}^2 \\
\phi_{1,2}^1 & \phi_{1,2}^2
\end{pmatrix}
\]  
(2.18)

Expanding equation (2.18) yields four conditions,

\[
\begin{align*}
\lambda_5 \bar{z}_1^0 &= \lambda_5 \bar{z}_1^0 \phi_{1,1}^1 + \lambda_5 \bar{z}_1^0 \phi_{1,2}^1; \\
0 &= \lambda_5 \bar{z}_1^0 \phi_{1,1}^2 + \lambda_5 \bar{z}_1^0 \phi_{1,2}^2; \\
0 &= \lambda_5 \bar{z}_2^0 \phi_{2,1}^1 + \lambda_5 \bar{z}_2^0 \phi_{2,2}^1; \\
\lambda_5 \bar{z}_2^0 &= \lambda_5 \bar{z}_2^0 \phi_{2,1}^2 + \lambda_5 \bar{z}_2^0 \phi_{2,2}^2.
\end{align*}
\]  
(2.19)

Under the conditions that \( \lambda_5 \bar{z}_1^0 \neq 0 \) and \( \lambda_5 \bar{z}_2^0 \neq 0 \), we have

\[
\begin{align*}
1 &= \phi_{1,1}^1 + \phi_{1,2}^1; \\
0 &= \phi_{1,1}^2 + \phi_{1,2}^2; \\
0 &= \phi_{2,1}^1 + \phi_{2,2}^1; \\
1 &= \phi_{2,1}^2 + \phi_{2,2}^2.
\end{align*}
\]  
(2.20)
From equation (2.14), the II matrix in this case is

\[ \Pi = I_2 - \sum_{i=1}^{2} \Phi_i = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} - \begin{pmatrix} \phi_{1,1} & \phi_{1,2} \\ \phi_{2,1} \phi_{2,2} \end{pmatrix} = \begin{pmatrix} \phi_{1,1} - \phi_{1,2} & \phi_{1,2} - \phi_{2,2} \end{pmatrix} = 0 \] (2.21)

Therefore, the \textit{sums of coefficients} prior implies that a VAR system in first differences is appropriate. As \( \lambda_5 \) increases, more weight is put on the prior and the it is increasingly satisfied. In the limiting case where \( \lambda_5 \to \infty \), there are as many unit roots as variables and there is no cointegration. Since the constant term is excluded from prior specification, nonzero constant terms and thereby linearly trending drifts are allowed even in the limit.

\textbf{Dummy Initial Observation Prior}

It is sometimes reasonable to assume that there are fewer stochastic trends in the VAR system (2.1) than there are variables, i.e., there exist stable cointegrating relations among the trending series. To account for this, Sims (1993) adds an additional dummy observation in which all values of all variables are set to the corresponding presample averages \( (\bar{z}_i, i = 1, \ldots, m) \) and the value of constant to 1. The prior, known in the literature as the \textit{dummy initial observation} prior, introduces correlation among coefficients on different variables in a given equation including the constant term. It allows for cointegration while maintaining the unit-root nonstationarity in all variables.

For the simple case of two variables and two lags in equation (2.15), the \textit{dummy initial observation} prior in the \( i \)-th equation is \( (\bar{z}_i^0) \) for the dependent variable and \( (1, \bar{z}_1^0, \bar{z}_2^0, \bar{z}_1^0, \bar{z}_2^0) \) for the independent variables. A scale factor of \( \lambda_6 \geq 0 \) is assigned to this dummy observation. The following equality holds under the
dummy initial observation prior,

\[
\begin{pmatrix}
\lambda_6 \tilde{z}_1^0 & \lambda_6 \tilde{z}_2^0
\end{pmatrix} = \begin{pmatrix} 1 \\ c_1 \\ c_2 \end{pmatrix} + \begin{pmatrix}
\lambda_6 \tilde{z}_1^0 & \lambda_6 \tilde{z}_2^0
\end{pmatrix} \begin{pmatrix}
\phi_{1,1}^1 & \phi_{2,1}^1 \\
\phi_{1,1}^2 & \phi_{2,1}^2
\end{pmatrix}
\]

\[+ \begin{pmatrix}
\lambda_6 \tilde{z}_1^0 & \lambda_6 \tilde{z}_2^0
\end{pmatrix} \begin{pmatrix}
\phi_{1,2}^1 & \phi_{2,2}^1 \\
\phi_{1,2}^2 & \phi_{2,2}^2
\end{pmatrix}.
\]

Expanding equation (2.22) yields,

\[
\begin{aligned}
\lambda_6 \tilde{z}_1^0 &= c_1 + \lambda_6 \tilde{z}_1^0 \phi_{1,1}^1 + \lambda_6 \tilde{z}_2^0 \phi_{2,1}^1 + \lambda_6 \tilde{z}_1^0 \phi_{1,2}^1 + \lambda_6 \tilde{z}_2^0 \phi_{2,2}^1; \\
\lambda_6 \tilde{z}_2^0 &= c_2 + \lambda_6 \tilde{z}_1^0 \phi_{1,1}^2 + \lambda_6 \tilde{z}_2^0 \phi_{2,1}^2 + \lambda_6 \tilde{z}_1^0 \phi_{1,2}^2 + \lambda_6 \tilde{z}_2^0 \phi_{2,2}^2.
\end{aligned}
\]

Under the condition that \( \lambda_6 \neq 0 \), we have

\[
\begin{pmatrix}
\tilde{z}_1^0 \\
\tilde{z}_2^0
\end{pmatrix} = \frac{1}{\lambda_6} \begin{pmatrix} c_1 \\ c_2 \end{pmatrix} + \begin{pmatrix}
\phi_{1,1}^1 + \phi_{1,2}^1 & \phi_{2,1}^1 + \phi_{2,2}^1 \\
\phi_{1,1}^2 + \phi_{1,2}^2 & \phi_{2,1}^2 + \phi_{2,2}^2
\end{pmatrix} \begin{pmatrix}
\tilde{z}_1^0 \\
\tilde{z}_2^0
\end{pmatrix},
\]

or,

\[
\begin{pmatrix}
1 - (\phi_{1,1}^1 + \phi_{1,2}^1) & - (\phi_{2,1}^1 + \phi_{2,2}^1) \\
-(\phi_{1,1}^2 + \phi_{1,2}^2) & 1 - (\phi_{2,1}^2 + \phi_{2,2}^2)
\end{pmatrix} \begin{pmatrix}
\tilde{z}_1^0 \\
\tilde{z}_2^0
\end{pmatrix} = \frac{1}{\lambda_6} \begin{pmatrix} c_1 \\ c_2 \end{pmatrix}.
\]

As \( \lambda_6 \rightarrow \infty \), the right hand side of equation (2.25) converges to zero, so that

\[
\begin{pmatrix}
1 - (\phi_{1,1}^1 + \phi_{1,2}^1) & - (\phi_{2,1}^1 + \phi_{2,2}^1) \\
-(\phi_{1,1}^2 + \phi_{1,2}^2) & 1 - (\phi_{2,1}^2 + \phi_{2,2}^2)
\end{pmatrix} \begin{pmatrix}
\tilde{z}_1^0 \\
\tilde{z}_2^0
\end{pmatrix} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}.
\]

Since \( \tilde{z}_1^0 \) and \( \tilde{z}_2^0 \) are non-zero values,

\[
\begin{aligned}
1 - (\phi_{1,1}^1 + \phi_{1,2}^1) &= -k (\phi_{1,1}^2 + \phi_{1,2}^2), \\
-(\phi_{2,1}^1 + \phi_{2,2}^1) &= k [1 - (\phi_{2,1}^2 + \phi_{2,2}^2)],
\end{aligned}
\]

(2.27)
where $k$ is a nonzero constant. From equation (3.14), the $\Pi$ matrix is

$$
\Pi = I_2 - \sum_{i=1}^{2} \Phi_i = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} - \begin{pmatrix} \phi_{1,1} & \phi_{1,2} \\ \phi_{2,1} & \phi_{2,2} \end{pmatrix} - \begin{pmatrix} \phi_{1,1}^2 & \phi_{1,2}^2 \\ \phi_{2,1}^2 & \phi_{2,2}^2 \end{pmatrix} = \begin{pmatrix} 1 - (\phi_{1,1} + \phi_{1,2}) & -(\phi_{2,1} + \phi_{2,2}) \\ -(\phi_{1,1}^2 + \phi_{1,2}^2) & 1 - (\phi_{2,1}^2 + \phi_{2,2}^2) \end{pmatrix}.
$$

It is clear that when conditions in (2.27) holds, the rank of $\Pi$ is one, i.e., there is a single cointegrating vector. Therefore, in the limiting case where $\lambda_6 \to \infty$, the dummy initial observation prior implies that more weight is put on a VAR where all series share the same stochastic trend and the intercept approaches zero. The sums of coefficients and dummy initial observation priors, when imposed together, favor unit roots with a single cointegrating relationship.

2.3 Regional Construction / Housing Modeling and Forecasting

2.3.1 Regional Construction / Housing Modeling

Regional construction / housing models fall into two strands of practice. One strand imitates national macroeconomic models and analyzes regional fixed investment along the lines of income and product accounts theory. An example is found in Ghali and Renaud (1975). A major component of the investment block in the Ghali and Renaud model is residential construction. Their model for residential construction is,

$$
I_r = -45.19 + 0.072(0.8GSP + 0.2GSP_{-1}) - 780.95p_{-1} + 5.19* FHA, \tag{2.29}
$$

where $I_r$ is the annual real value of residential construction, GSP is the annual real gross state product, $p$ is the percentage change of residential homes multilistings prices, and FHA is the mortgage rate. Note however that two regression
coefficients have wrong signs: \( \hat{p} \) supposedly captures the positive effects on investment of an expected appreciation in home values. FHA measures the financing cost and is expected to be negatively correlated with construction investment. Ermini (1991) re-estimates the same model over a longer sample period (1958-1990) and obtains more reasonable parameter values,

\[
I_t = 199.3 + 0.037(0.8GSP + 0.2GSP_{-1}) + 4.78p_{-1} - 15.02*\text{FHA}. \quad (2.30)
\]

Nevertheless, Ermini finds that the regression residual contain a unit root, and equation (2.30) is subject to the "spurious regression" problem. (Granger and Newbold, 1974).

The first strand of practice suffers from severe data limitation. Income-side Gross State Product (GSP) account data at the state level are available from BEA only at annual frequency after significant lags and are not available at all at other subnational levels. Expenditure-side GSP data as required by the estimation of equation (2.30) is available only after re-construction.\(^5\) As such, it is empirically impossible to conduct model updates in a timely manner for forecasting purposes.

The second strand of practice has some advantages in this respect. Instead of relying on income and product account theory, models in this category draw heavily from neoclassical consumption theory and use data readily available from standard statistical agencies. The theory postulates that rational consumers attempt to maximize their utility with respect to different goods and services, including housing, that they can purchase within the constraints imposed by market and their income. A household "chooses" between housing and nonhousing commodities. The household's attempt to maximize its utility with respect to housing and nonhousing goods defines its housing demand equation. In general, a housing demand equation can be specified as,

\[
Q = q(Y, P^h, P^o, T), \quad (2.31)
\]

\(^5\)Not every state does the re-construction, however. Hawaii happens to be one of the states that does, see Oshima (1965), Shang, Albrecht, and Ifuku (1970) and DBEDT (1989).
where $Q$ is consumption on housing service, $Y$ is household income, $P^h$ is the price of housing, $P^o$ is a vector of prices of other goods and services, and $T$ is a vector of taste factors. Some studies (for instance, Olsen 1969) incorporate a vector of household characteristics, $H$, in the housing demand equation, including household demographics such as age, race, marital status, and household composition. These factors capture differences in consumer preferences unrelated to income and price factors. Thus, equation (2.31) is alternatively put as,

$$Q = q(Y, P^h, P^o, H).$$

The model in (2.32) is empirically estimated using data from standard statistical agencies such as BEA and BLS. A typical example is found in the Florida modeling system described in Fullerton and West (1998). In their construction activity block, principal drivers of regional housing starts include net migration, proxy variables for regional affordability indices, mortgage rates, consumer confidence, unemployment, employment growth, population distribution by age cohorts, an index of five-year building trends relative to state household growth, average values per unit built, and national housing starts.

### 2.3.2 Regional Construction / Housing Forecasting

It is not until recently that forecasts from regional construction models have been subjected to systematic evaluations. Fullerton and his colleagues examine the ex ante quarterly forecasts for total housing starts in Florida and its six largest MSAs between 1985 and 1995 in a series of papers (Fullerton and West, 1998; Fullerton, Luevano, and West, 2000; Fullerton, Laaksonen, and West, 2001; and Fullerton, 2001). They compare housing starts forecasts from a structural multi-equation system (as described earlier) to those from univariate ARIMA models and the simple random walk model at one- to ten-quarter ahead forecast lengths. The six MSAs chosen have diversified construction markets and underlying economic bases so that it is less likely that housing start forecasts are dominated by any
particular sector. A modified Theil inequality coefficient is used to evaluate forecast accuracy.\(^6\) Fullerton et. al. find that the structural model performs competitively against the univariate ARIMA benchmark, but the competitive edge decreases when the structural model is compared to the random walk specification. A further decomposition of total housing into single-family and multi-unit dwellings reveals that the structural model does not offer a competitive specification for either category.

Findings by Fullerton et. al. are not surprising. McNees (1986) and Litterman (1986) have long noticed the unsatisfactory forecasting performance of large-scale macroeconomic models at the national level and recommended the use of alternative low-cost BVAR specification. In the literature, BVAR housing models are found at both the national and regional levels. Dua and Smyth (1995) construct several BVAR models to study the determining factors of U.S. home sales. They find that households' buying attitudes do not add much to the forecasting capability of a BVAR model that already incorporates other economic factors like the price of homes, the mortgage rate, real personal disposable income, and the unemployment rate. This implies that information embedded in the buying attitudes is already contained in the set of aforementioned economic variables. Dua, Miller, and Smith (1999) extend the basic five-variable BVAR model to include various leading indicators. The six leading indicators tested are: building permits authorized, housing starts, U.S. Department of Commerce's composite index of eleven leading indicators, the short- and long-leading indices developed by the Center for International Business Cycle Research (CIBCR) at Columbia University, and another leading index constructed by CIBCR that focuses solely on employment related variables. They find that the model which uses authorized building permits as a leading indicator consistently produces the most accurate forecasts. All models use pure Minnesota priors.

At the regional level, Dua and Miller (1996) estimate a BVAR with Minnesota prior for Connecticut home sales. Similar to the national model, interest is on

\(^6\)The Theil's U statistic is defined as the ratio of the Root Mean Squared Error (RMSE) of a given model forecast to the RMSE of the forecasts from an ARIMA model.
home sales forecasts, evaluated using Theil's U-statistics at one- through six-quarter ahead. The explanatory variables used include a Connecticut 30-year fixed mortgage rate and a constant-quality home price index constructed by the Center for Real Estate and Urban Economics Studies at the University of Connecticut. The main objective is to compare the forecasting capability of composite indices relative to that of single-series economic indicators in a BVAR setting. For this purpose, Dua and Miller (1996) construct a coincident index—comprised of the total unemployment rate, the insured unemployment rate, nonfarm employment, and total employment, and a leading index—consisting of the average workweek of production workers, the short-duration (less than 15 weeks) unemployment rate, the initial claims for unemployment insurance, help-wanted advertising for Hartford, and total housing permits authorized. They find that the use of coincident and leading indices not only saves degrees of freedom but also generates superior forecasts. Empirically this might be explained by the larger information set contained in coincident and leading indices than that in any single variable series.

2.4 A BVAR Forecasting Model for Hawaii Construction Activity

The BVAR methodology has evolved since Dua et. al. applied it to the housing market. Priors on linear combinations of the parameters are added to partially mitigate the pure random walk assumptions and account for interactions both within and across variables in the system. Robertson and Tallman (1999) estimate a six-variable U.S. macroeconometric forecasting model with the sums of coefficients and dummy initial observation priors. They compare the model to other VAR and BVAR specifications and find that it generally yields the best forecasts.

This paper uses the dummy priors in a high-frequency regional construction forecasting model and evaluate to what extent forecast accuracy is improved by
incorporating these priors. The section describes the model specification and is organized as follows: Section 2.4.1 discusses the choice of variables and tests for order of integration; Section 2.4.2 illustrates the prior selection criterion and lists estimation results.

2.4.1 Selection of Variables

For the Hawaii construction model under consideration, multiple series are used to characterize construction activity. Home sales is by far the most intuitive indicator and is measured by the total number of resales for single-family units and condominiums as reported by Prudential-Locations Research Department. Construction jobs and the contracting general excise tax (GET) base are included to measure construction activity in general. Figure 2.1 plots home resale volume ($kh_{hi}$), resale price ($ph_{hi}$), construction jobs ($ec_{hi}$), and the contracting GET base ($txconbs_{hi}$) in logarithms. Although the sample period is relatively short (with only 84 quarterly observations), an investment cycle is largely in shape. Following anemic activity in the first half of the 1980s, the construction industry expanded at a rapid pace during the second half riding on the Japanese investment boom. However, a sharp drop came in the early 1990s after Japanese real estate and investment bubble burst. For most of the 1990s, the industry remained flat. It is not until later half of the decade that we see a small turnaround, but more in the resale volume than in price or value.

Economic theory reviewed in section 2.3.1 suggests that several factors may explain the fluctuations in construction, including household income, mortgage interest rates, and the current and expected future economic conditions. In this paper, state personal income from the BEA is used to measure household purchasing power. The U.S. 30-year conventional mortgage rate from the Federal Reserve Bank at St. Louis is used to measure the cost of financing. Besides these, unemployment rate is also included as a comprehensive indicator of the labor market because it has large impacts on consumer's willingness to take on mortgage-financed large-item consumption. Figure 2.2 plots the Hawaii home
Figure 2.1: Hawaii Construction Activity 1980Q1-2000Q4
resale volume against the unemployment rate. Home resale volume seems to be negatively correlated with the unemployment rate.

Expectations on future economic conditions also influence construction, one good indicator of which is total building permits authorized (Dua, Miller, and Smyth, 1999). A building permit represents the intention to build in the future. When general expectations on future economic conditions are positive, people are more willing to make fixed investments and building permits increase. In this paper, I use two kinds of permit indicators reported by the State of Hawaii Department of Business Economic Development & Tourism (DBEDT). The first is total private building permits authorized. The second is government contracts awarded. The sum of the two series measures overall building intention in Hawaii. Figure 2.3 plots Hawaii home resale volume ($kh_{hi}$) against the overall building permits issued ($ph_{hi}$).

Compared with other states, Hawaii relies more heavily on the tourism sector.
Figure 2.3: Hawaii Home Resales Against Building Permits 1980Q1-2000Q4
A considerable amount of construction activity comes from building and renovating hotels and other rental facilities to accommodate visitors from all over the world. I therefore include an additional variable to measure the impacts of tourism on construction—total visitor arrivals to the islands. Table 2.1 below summarizes all variable definitions and data sources. Monthly series are aggregated to quarterly. Seasonally unadjusted series are adjusted using standard BEA X11 procedures. All series except the mortgage rate ($rmort.us$) and Hawaii unemployment rate ($ur_hi$) enter the model in logarithms. Table 2.2 lists the correlation among model series over full sample period 1980Q1–2000Q4.

### Table 2.1: Variables in the Hawaii Construction Model

<table>
<thead>
<tr>
<th>Mnemonic</th>
<th>Description</th>
<th>Units</th>
<th>Freq.</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>ecns_hi</td>
<td>Hawaii construction sector jobs</td>
<td>000s</td>
<td>M</td>
<td>BLS</td>
</tr>
<tr>
<td>khns_hi</td>
<td>Hawaii single-family and condominium resales</td>
<td>Units</td>
<td>Q</td>
<td>PRUD</td>
</tr>
<tr>
<td>txconbsns_hi</td>
<td>Hawaii contracting GET base</td>
<td>000$</td>
<td>M</td>
<td>DTAX</td>
</tr>
<tr>
<td>kpns_hi</td>
<td>Hawaii private and public building permits</td>
<td>Mil.$</td>
<td>Q</td>
<td>DBEDT</td>
</tr>
<tr>
<td>rmort_us</td>
<td>U.S. 30 year conventional mortgage rate</td>
<td>%</td>
<td>M</td>
<td>FED</td>
</tr>
<tr>
<td>yp_hi</td>
<td>Hawaii personal income</td>
<td>Mil.$</td>
<td>Q</td>
<td>BEA</td>
</tr>
<tr>
<td>urns_hi</td>
<td>Hawaii civilian unemployment rate</td>
<td>%</td>
<td>M</td>
<td>BLS</td>
</tr>
<tr>
<td>visns_hi</td>
<td>Total visitor arrivals to Hawaii</td>
<td>000s</td>
<td>M</td>
<td>DBEDT</td>
</tr>
</tbody>
</table>

PRUD: Prudential Locations research department, State of Hawaii.
DTAX: Department of Taxation, State of Hawaii.
FED: Federal Reserve Bank at St. Louis, U.S.
BEA: Bureau of Economic Analysis, U.S.

### Unit Root Tests

In this paper, the order of integration of a series is established by testing for unit roots in the autoregressive processes using *Dickey-Fuller* (DF) and *augmented Dickey-Fuller* (ADF) tests (Dickey and Fuller, 1979, 1981). Table 2.3 lists the standard DF and ADF(5) test statistics when a constant and a trend are included in the specification. From the table, the null of unit root cannot be rejected for
all variables in levels. When variables are first differenced, ADF(5) test statistics reject the null of unit root for all except Hawaii personal income ($yp_{hi}$) and unemployment rate ($ur_{hi}$). A closer look at the regressions for $\Delta ur_{hi}$ indicates that the residuals from the DF test are serially uncorrelated. In this case, the DF test is sufficient and we reject the null of non-stationarity at 5% level.

The non-rejection of a unit root in $\Delta y_{p,hi}$ might be caused by a slowdown in Hawaii personal income growth during the 1990s (see figure 2.4). Hawaii income growth averaged 2% during the 1980s and early 1990s, whereas the number falls to around 1% in the latter part of 1990s. In addition, Hawaii personal income drops significantly in 1992Q3 when Hurricane Iniki hit the islands. Perron (1989, 1990) argues that a structural change in the mean of a stationary variable tends to bias the usual unit root tests towards non-rejection of the null of unit root. I therefore perform the Perron (1990) test for unit root on $\Delta y_{p,hi}$. I pick the break point to be 1992Q3. The Perron test is performed in two steps: First, $\Delta y_{p,hi}$ is regressed on a constant and a step variable $S_t$ which takes the value of 1 for $t \geq 1992Q3$ and 0 otherwise. Second, the difference of regression residuals ($\Delta e_t$) from the first step is regressed on the first lag of regression residuals ($e_{t-1}$) and a pulse variable $P_t$ which equals 1 for $t = 1992Q3$ and 0 otherwise. Lags of $\Delta e_t$ may be added to the second step regression to whiten regression errors. Stationarity of $\Delta y_{p,hi}$ is established by a significantly negative parameter on $e_{t-1}$. For $yp_{hi}$, the Perron test produces a parameter value of -4.612 which is below the 5% significance level.
Table 2.3: Time Series Property of the Data – ADF Unit Root Test

\[
\text{DF: } \Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \epsilon_t \\
\text{ADF: } \Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \sum_{i=1}^{5} \delta_i \Delta y_{t-i} + \epsilon_t \\
H_0 : \gamma = 0
\]

<table>
<thead>
<tr>
<th>Variables</th>
<th>DF</th>
<th>ADF(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ee_hi</td>
<td>-1.130</td>
<td>-1.824</td>
</tr>
<tr>
<td>kh_hi</td>
<td>-2.200</td>
<td>-2.140</td>
</tr>
<tr>
<td>txconbs_hi</td>
<td>-1.398</td>
<td>-1.549</td>
</tr>
<tr>
<td>kp_hi</td>
<td>-2.674</td>
<td>-1.252</td>
</tr>
<tr>
<td>yp_hi</td>
<td>-0.641</td>
<td>-1.044</td>
</tr>
<tr>
<td>ur_hi</td>
<td>-0.892</td>
<td>-1.694</td>
</tr>
<tr>
<td>vis_hi</td>
<td>-1.879</td>
<td>-1.401</td>
</tr>
<tr>
<td>rmort_us</td>
<td>-1.823</td>
<td>-1.600</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Variables</th>
<th>DF</th>
<th>ADF(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>\Delta ec_hi</td>
<td>-6.168</td>
<td>-3.879</td>
</tr>
<tr>
<td>\Delta kh_hi</td>
<td>-8.932</td>
<td>-3.479</td>
</tr>
<tr>
<td>\Delta txconbs_hi</td>
<td>-10.321</td>
<td>-3.575</td>
</tr>
<tr>
<td>\Delta kp_hi</td>
<td>-13.996</td>
<td>-4.953</td>
</tr>
<tr>
<td>\Delta yp_hi</td>
<td>-12.732</td>
<td>-2.001</td>
</tr>
<tr>
<td>\Delta ur_hi</td>
<td>-4.462</td>
<td>-2.555</td>
</tr>
<tr>
<td>\Delta vis_hi</td>
<td>-10.633</td>
<td>-4.051</td>
</tr>
<tr>
<td>\Delta rmort_us</td>
<td>-6.947</td>
<td>-5.261</td>
</tr>
</tbody>
</table>

Note: Column 1 gives the target series (dependent variable in equations DF and ADF). Column 2 is the Dick-Fuller test statistic for \( H_0 \). Column 3 is the Augmented Dick-Fuller statistic for \( H_0 \). All variables except \( ur_{hi} \) and \( rmort_{us} \) are in logarithms. Boldness indicates significance at 5% level where critical value is -3.45.
I therefore conclude that all variables used in the model are I(1) series. Figure 2.5 and 2.6 plot the series in levels and first differences.

2.4.2 Prior-choosing Criterion and Estimation Results

From section 2.2, there are six hyper-parameters to be determined in a BVAR model with sums of coefficients and dummy initial observation priors: the overall tightness ($\lambda_1$), the relative tightness of other variables to the dependent variable ($\lambda_2$), the lag decay parameter ($\lambda_3$), the tightness on constant ($\lambda_4$), the weight on the sums of coefficients prior ($\lambda_5$), and the weight on the dummy initial observation prior ($\lambda_6$). These hyper-parameters are picked using the General Forecast Error Second Moment Matrix (GFESM) criterion proposed in Clements and Hendry (1998). The GFESM criterion is characterized by minimizing the log determinant of the variance-covariance matrix of the one- to $h$-quarter ahead forecast errors. Compared to the widely adopted Mean Squared Forecast Error (MSFE) and Theil’s
Figure 2.5: Variables in the Hawaii Construction Model (Levels)
Figure 2.6: Variables in the Hawaii Construction Model (First Differences)
U statistic criteria, GFESM has the advantage of being invariant to non-singular, scale-preserving linear transformations (Clements and Hendry, 1998).

The Hawaii BVAR construction model is estimated using data from 1980Q1 to 1995Q4, leaving 20 observations for ex post forecast evaluation. Rolling samples are used in picking priors. The model is first estimated using data over the 1980Q1–1995Q4 sample period. One- to eight-quarters ahead forecast errors for the three variables of interest (echi, kh_hi, txconsbs_hi) are generated to form an 8 x 3 error vector (et). The error variance-covariance matrix and its log determinant are calculated as \( \Phi = E[e_t e'_t] \) and \( \log|\Phi| \), call this \( \log|\Phi|_1 \). Next, the sample period is extended by one quarter to 1996Q1 and the model is re-estimated. Another set of one- to eight-quarters ahead forecast errors are used to calculate a new log determinant \( \log|\Phi|_2 \). This process is repeated 13 times until we reach 1998Q4 and the eight-quarters ahead forecasts reach the end of sample period 2000Q4. We then calculate the simple mean \( (\log|\Phi|_{\text{mean}}) \) of all the log determinants, \( \log|\Phi|_1, \log|\Phi|_2, \ldots, \log|\Phi|_{13} \). Our objective is to loop through different prior specifications and find the minimum \( \log|\Phi|_{\text{mean}} \).

For the Hawaii construction model, we set the initial prior selection range to huddle around priors used in Litterman (1986) and Robertson and Tallman (1999), i.e., the overall tightness parameter \( \lambda_1 \) from 0.1 to 0.5 with an increment of 0.1; the relative tightness parameter \( \lambda_2 \) from 0.1 to 0.5 with an increment of 0.1; the lag decay parameter \( \lambda_3 \) from 0.2 to 1 with an increment of 0.2; the tightness on constant \( \lambda_4 \) from 0.1 to 0.5 with an increment of 0.1; the weight on the sums of coefficients prior \( \lambda_5 \) from 3 to 7 with an increment of 1, and the weight on the dummy initial observation prior \( \lambda_6 \) from 3 to 7 with an increment of 1. Altogether there are 15,625 different combinations of prior specifications. The selection program runs for about seven hours in Matlab on a Pentium III 900 MHz PC computer. It results in the parameter selections listed in table 2.4.

All selected priors fall on the boundary of the selection range other than the

---

7The sample is relatively short in capturing long-term construction trend, but it does cover the building boom experienced in the first half of 1980s and the subsequent stagnancy. Data availability exerts the limit here. There is no tax base data for the pre-1980 period.
Table 2.4: Priors Selected for the Hawaii Construction Model: 1st Round

<table>
<thead>
<tr>
<th>Prior</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\lambda_1$</td>
<td>Overall tightness</td>
<td>0.2</td>
</tr>
<tr>
<td>$\lambda_2$</td>
<td>Relative tightness</td>
<td>0.5</td>
</tr>
<tr>
<td>$\lambda_3$</td>
<td>Leg decay</td>
<td>1.0</td>
</tr>
<tr>
<td>$\lambda_4$</td>
<td>Tightness on constant</td>
<td>0.1</td>
</tr>
<tr>
<td>$\lambda_5$</td>
<td>Sums of coefficient</td>
<td>3.0</td>
</tr>
<tr>
<td>$\lambda_6$</td>
<td>Dummy initial observation</td>
<td>3.0</td>
</tr>
</tbody>
</table>

overall tightness. Holding overall tightness $\lambda_1 = 0.2$, I reset the selection range to: relative tightness $\lambda_2$ from 0.5 to 1 with an increment of 0.1; the lag decay parameter $\lambda_3$ from 1 to 2 with an increment of 0.2; the tightness on constant $\lambda_4$ from 0.02 to 0.1 with an increment of 0.02; the weight on the sums of coefficients prior $\lambda_5$ from 0.02 to 0.1 with an increment of 0.02, and the weight on the dummy initial observation prior $\lambda_6$ from 0.02 to 0.1 with an increment of 0.02. The final combination of priors selected are listed in table 2.5.

Table 2.5: Priors Selected for the Hawaii Construction Model: 2nd Round

<table>
<thead>
<tr>
<th>Prior</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\lambda_1$</td>
<td>Overall tightness</td>
<td>0.2</td>
</tr>
<tr>
<td>$\lambda_2$</td>
<td>Relative tightness</td>
<td>1</td>
</tr>
<tr>
<td>$\lambda_3$</td>
<td>Leg decay</td>
<td>1.4</td>
</tr>
<tr>
<td>$\lambda_4$</td>
<td>Tightness on constant</td>
<td>0.02</td>
</tr>
<tr>
<td>$\lambda_5$</td>
<td>Sums of coefficient</td>
<td>0.08</td>
</tr>
<tr>
<td>$\lambda_6$</td>
<td>Dummy initial observation</td>
<td>0.02</td>
</tr>
</tbody>
</table>

Our results imply that we have strong priors on the constant and the random walk approximation for the right-hand-side variable. Prior variances on other variables are treated the same as those on the dependent variable. Higher order lags follow a decay pattern faster than harmonic decay. Finally, neither dummy priors seem strong enough. Figure 2.7 through 2.9 plot the one-quarter ahead forecast errors for construction jobs (ec.hi), the number of home resales (kh.hi),
Figure 2.7: One-quarter Ahead Forecast Error for Hawaii Construction Jobs 1996Q1-2000Q4 and GET contracting tax base (txconbs_hi) for 1996Q1–2000Q4. Compared with historical standard deviations, the forecast errors are relative small. The historical standard deviation over sample period 1980Q1–1995Q4 is 0.2557 for ec_hi, 0.3610 for kh_hi and 0.4590 for txconbs_hi.

2.5 Forecast Evaluation

This section evaluates the forecasting performance of the newly established BVAR Hawaii construction model. The intention is to investigate how prior restrictions on a VAR specification can influence forecasts at different horizons. Specifically, attention is focused on three variables: construction jobs (ec_hi), the number of home resales (kh_hi) and the GET contracting tax base for Hawaii (txconbs_hi). The BVAR model with sums of coefficients and dummy initial
Figure 2.8: One-quarter Ahead Forecast Error for Hawaii Home Resales 1996Q1-2000Q4
Figure 2.9: One-quarter Ahead Forecast Error for Hawaii Contracting GET Tax Base 1996Q1-2000Q4
observation priors estimated in section 2.4 serves as the benchmark (denoted as BVAR-Coint model). Forecasts from the BVAR-Coint model are then compared to forecasts from the following competing specifications:

1. An unrestricted VAR specification in the levels of series with lag length $k = 5$, estimated by OLS. This specification is denoted as the VAR model;

2. An unrestricted VAR specification in the first differences of series, estimated by OLS with $k = 5$. This specification is equivalent to a sums of coefficients prior imposed exactly. It is denoted as the DVAR model;

3. A Minnesota prior VAR in levels as described in section 2.2.1. The settings for the hyper parameters are the same as those for the BVAR with linear combination prior model: overall tightness $\lambda_1 = 0.2$; relative tightness $\lambda_2 = 1$; lag decay $\lambda_3 = 1.4$ and tightness on constant $\lambda_4 = 0.02$. It is denoted as the BVAR model. Note that by setting the priors to be the same as BVAR-Coint model, the evaluation biases against the Minnesota BVAR model since the prior choice is not optimized.

The different VAR models are first fit over the sample period from 1980Q1 to 1995Q4, with the five presample values being those for 1980Q1 to 1981Q1. The VAR models are then re-estimated every quarter by extending the estimation sample period by one quarter until the end of the sample data is reached. In doing so, coefficient estimates may vary in response to new data. Every time the model is re-estimated, forecasts for construction jobs (ec_hi), number of resales (kh_hi), and the GET contracting tax base (txconbs_hi) are generated for one, two, four and eight quarters ahead. Pooling the forecast errors for each period yields a set of 20 one-quarter ahead forecasts, 19 two-quarters ahead forecasts, 17 four-quarters ahead forecasts, and 13 eight-quarters ahead forecasts. The RMSE results for one-, two-, four- and eight-quarters ahead forecast errors are reported in table 2.6. Numbers in parentheses give the ratio of the RMSE of the associated model to the RMSE of the BVAR-Coint model. A value greater than one for the ratio
means that the RMSE of the given model is larger than that for the cointegration BVAR and therefore indicating less accurate forecasts.

Table 2.6: RMSE of VAR Specifications 1997Q1–2000Q4

<table>
<thead>
<tr>
<th>Models</th>
<th>One-quarter</th>
<th>Two-quarters</th>
<th>Four-quarters</th>
<th>Eight-quarters</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Construction Jobs</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>VAR</td>
<td>0.0408 (2.39)</td>
<td>0.0613 (2.47)</td>
<td>0.0895 (2.86)</td>
<td>0.0857 (2.04)</td>
</tr>
<tr>
<td>DVAR</td>
<td>0.0449 (2.63)</td>
<td>0.0439 (1.77)</td>
<td>0.0338 (1.08)</td>
<td>0.0358 (0.85)</td>
</tr>
<tr>
<td>BVAR</td>
<td>0.0200 (1.17)</td>
<td>0.0316 (1.27)</td>
<td>0.0475 (1.52)</td>
<td>0.0934 (2.22)</td>
</tr>
<tr>
<td>BVAR-Coint</td>
<td>0.0171</td>
<td>0.0248</td>
<td>0.0312</td>
<td>0.0421</td>
</tr>
<tr>
<td><strong>Home Resale Volume</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>VAR</td>
<td>0.1230 (1.28)</td>
<td>0.2332 (1.31)</td>
<td>0.3922 (1.36)</td>
<td>0.8275 (2.03)</td>
</tr>
<tr>
<td>DVAR</td>
<td>0.1476 (1.44)</td>
<td>0.1278 (0.68)</td>
<td>0.1178 (0.41)</td>
<td>0.1255 (0.35)</td>
</tr>
<tr>
<td>BVAR</td>
<td>0.1238 (1.29)</td>
<td>0.1418 (0.80)</td>
<td>0.1361 (0.47)</td>
<td>0.1560 (0.38)</td>
</tr>
<tr>
<td>BVAR-Coint</td>
<td>0.0960</td>
<td>0.1776</td>
<td>0.2882</td>
<td>0.4074</td>
</tr>
<tr>
<td><strong>Hawaii GET Contracting Tax Base</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>VAR</td>
<td>0.1147 (1.79)</td>
<td>0.1866 (2.53)</td>
<td>0.2967 (3.07)</td>
<td>0.3810 (5.53)</td>
</tr>
<tr>
<td>DVAR</td>
<td>0.0856 (1.34)</td>
<td>0.1019 (1.38)</td>
<td>0.1068 (1.10)</td>
<td>0.0973 (1.41)</td>
</tr>
<tr>
<td>BVAR</td>
<td>0.0697 (1.09)</td>
<td>0.0828 (1.12)</td>
<td>0.1058 (1.09)</td>
<td>0.0762 (1.11)</td>
</tr>
<tr>
<td>BVAR-Coint</td>
<td>0.0640</td>
<td>0.0738</td>
<td>0.0967</td>
<td>0.0689</td>
</tr>
</tbody>
</table>

Note: Column 1 lists the different VAR specifications; Column 2 to 5 gives the RMSE of one-, two-, four- and eight-step ahead forecast errors. Numbers in parentheses give the ratio of the RMSE of the associated model to the RMSE of the BVAR-Coint model at each horizon. A value greater than one means that the RMSE of the given model is larger than that of the BVAR-Coint model, indicating that the given model's forecast is less accurate than that of the BVAR-Coint model.

From table 2.6, the BVAR-Coint model generates superior forecasts for \textit{ec.hi} and \textit{txconbs.hi} at all horizons but eight-quarters ahead for \textit{ec.hi}. The BVAR and DVAR models perform very well for home resale volume in the medium to long horizon, but generates relatively poor forecasts one-quarter ahead. The unrestricted VAR model is clearly dominated by all the other VAR specifications. The results are discussed in details below.

\textit{Hawaii Construction Jobs.} The BVAR-Coint model produces the most accurate forecasts for construction jobs at one-, two- and four-quarters ahead. Compared to other VAR specifications, the RMSEs is at least 8% lower at these horizons.
Nevertheless, the competitive edge of the BVAR-Coint model against the DVAR model decreases as the forecast horizon rises. At eight-quarter ahead, the RMSE from BVAR-Coint model is 15% larger than that from the DVAR model. On the other hand, the relative forecast performance of the BVAR model decreases at longer forecast horizons. At one-quarters ahead, the RMSE of BVAR model is 17% higher than that from the BVAR-Coint model, increasing to 122% at eight-quarters ahead. The unrestricted VAR model performs very poorly at all horizons. Its RMSE is consistently more than double that from the BVAR-Coint model.

**Hawaii Home Resale Volume.** The forecast performance of different VAR models paints a very different picture for home resale volume. BVAR-Coint model generates the best forecasts only at one-quarter ahead, with a RMSE 29% and 44% lower than that from the BVAR and DVAR models. As the forecast horizon increases, the BVAR-Coint model quickly loses its competitiveness. Starting at two-quarters ahead, the BVAR-Coint model generates forecast errors higher than those from the two rival models. At eight-quarters ahead, the RMSE is more than 60% higher than those from the BVAR and DVAR models. The DVAR model, though producing inaccurate forecasts at one-quarter ahead, gains dominance at the other forecast horizon. RMSEs from the DVAR model are 32%, 59% and 65% lower than those from the BVAR-Coint model, and 12%, 6% and 3% lower than those from the BVAR model at two-, four-, and eight-quarters ahead. The unrestricted VAR model again generates the least accurate forecasts, with RMSE 103% higher than that of the BVAR-Coint model at eight-quarters ahead.

**Hawaii GET Contracting Tax Base.** The Hawaii contracting tax base is best forecasted by the BVAR-Coint model at all horizons. The relative performance of the BVAR model is stable over the entire forecast horizon with a RMSE 10% higher than that from BVAR-Coint model. The DVAR model in this case produces relatively less accurate forecasts except at the four-quarters ahead horizon. The RMSE difference between DVAR model and BVAR-Coint model averages to about 30% over the entire forecast range. The unrestricted VAR model consistently gives the worst forecasts, with RMSEs higher than that of the BVAR-Coint model by as much as 453% at eight-quarters ahead.
Table 2.7: Cointegration Rank Statistics

<table>
<thead>
<tr>
<th>$H_r$</th>
<th>Statistic</th>
<th>$0.05CV$</th>
<th>$0.10CV$</th>
<th>Statistic</th>
<th>$0.05CV$</th>
<th>$0.10CV$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$r = 0$</td>
<td>225.5</td>
<td>141.7</td>
<td>136.2</td>
<td><strong>60.14</strong></td>
<td>50.10</td>
<td>47.08</td>
</tr>
<tr>
<td>$r \leq 1$</td>
<td><strong>165.4</strong></td>
<td>108.9</td>
<td>103.7</td>
<td><strong>57.39</strong></td>
<td>43.72</td>
<td>40.94</td>
</tr>
<tr>
<td>$r \leq 2$</td>
<td>108</td>
<td>81.20</td>
<td>76.68</td>
<td><strong>41.34</strong></td>
<td>37.85</td>
<td>35.04</td>
</tr>
<tr>
<td>$r \leq 3$</td>
<td><strong>66.67</strong></td>
<td>56.43</td>
<td>52.71</td>
<td><strong>32.59</strong></td>
<td>31.68</td>
<td>29.00</td>
</tr>
<tr>
<td>$r \leq 4$</td>
<td>34.08</td>
<td>35.37</td>
<td>32.51</td>
<td>16.29</td>
<td>20.16</td>
<td>22.53</td>
</tr>
<tr>
<td>$r \leq 5$</td>
<td>13.92</td>
<td>18.08</td>
<td>15.82</td>
<td>12.09</td>
<td>13.92</td>
<td>15.82</td>
</tr>
</tbody>
</table>

Note: Column 1 lists the null hypothesis of zero, at least one, two, three, four, five 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; 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; Bolded numbers indicate significance.

The forecast performance of alternative VAR specifications considered here does not produce consistent conclusions across variables. Specifically, the BVAR-Coint model generates the best forecasts for Hawaii construction jobs and contracting tax base, whereas its pre-eminence drops with the increase of forecast horizon for home resales. This is in contrast with Robertson and Tallman (1999) who find a supremacy of BVAR with sums of coefficients and dummy initial observation priors for all variables involved in a six-variable U.S. macroeconomic forecasting model.\(^8\)

As a preliminary effort to understand the difference, I test for the cointegrating rank among the eight variables in the Hawaii construction model. Two variables are treated as weakly exogenous: the U.S. 30-year mortgage rate ($rmort.us$) and total visitor arrivals to Hawaii ($vis_hi$). Table 2.7 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, Shin, and Smith (2000) with two exogenous variables. From the table, the null of zero, one, two and three cointegrating relations are rejected at both the 5% and 10% levels. When it comes to the null of

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\(^8\)The six variables are U.S. real GDP, civilian unemployment rate, consumer price index (CPI), M2 money stock, effective federal funds rate and commodity price. The three variables evaluated include the unemployment rate, CPI inflation and GDP growth rate.
four cointegrating vectors, only the trace statistic rejects at 10% significance level. I therefore conclude that the system has four long-run cointegrating vectors.

On the other hand, by introducing the dummy initial observation prior into a BVAR specification, we implicitly assume that all series share the same stochastic trend, or equivalently, there exists only one cointegrating relationship. Therefore, for the Hawaii construction model, it is possible that construction jobs and contracting tax base cointegrate, but not with home resales. As forecast horizon increases, integrated forecast errors for home resales accumulate, leading to higher RMSEs than a stationary specification such as the DVAR model. If this is the case, a model specified in DVAR or BVAR in first differences might be preferred.

2.6 Concluding Remarks

Regional construction activity is important because it generates both original and derived demand for various local business sectors such as real estate credit-issuing agencies, retail chain stores, public utility, and municipal infrastructure. As such, construction forecasts are good indicators of future market conditions. Accurate construction forecasts are indispensable to effective planning and policy analysis.

Nevertheless, regional forecasting models devoted to construction are rare, not to mention the even smaller literature on construction forecast evaluations. This essay represents the first attempt in the literature to incorporate priors on linear combinations of parameters—namely, sums of coefficients prior and dummy initial observation prior— in a regional construction forecasting model. Inclusion of these priors partially mitigates the random walk specification in BVAR models and introduces cointegration. The state of Hawaii is used because of its rich data on GET contracting tax base. The contracting tax base offers a relatively accurate measure for all forms of construction activity.

Compared to the Connecticut model in Dua and Miller (1996), the Hawaii construction model includes as drivers not only the collective measures of local economic conditions such as personal income and civilian unemployment rate, but
also total visitor arrivals to Hawaii considering the dominant position held by tourism in the local economy. In this respect, the Hawaii construction model illustrate how the export base theory can be and should be incorporated into a regional forecasting model.

Forecasts from the BVAR model with linear combination priors are compared to those from alternative VAR specifications, including an unrestricted VAR in levels, an unrestricted VAR in first differences, and a BVAR with pure Minnesota priors. The results are mixed. The BVAR with linear combination priors generates the best forecasts for two out of three variables of interest: Hawaii construction jobs and the GET contracting tax base. Nevertheless, an unrestricted VAR in first differences produces the most accurate forecast for home resales especially at longer horizons. This is in contrast with Robertson and Tallman (1999) who find that a BVAR with linear combination priors dominates for all variables studied. The inferior forecasting performance for home resales might be explained by the limitation of a single cointegrating relationship imposed by the dummy initial observation prior.

Dua and Miller (1996) find that the use of coincident and leading indices in the regional housing model not only saves degrees of freedom but also generates superior forecasts. It is therefore an interesting study to apply their methodology to the Hawaii construction model with linear combination priors. By constructing coincident and leading indicators, we can effectively reduce the number of variables used in the model and potentially the dimension of cointegrating space that are non-stationary. A study as proposed not only verifies the applicability of Dua and Miller (1996)'s findings to the state of Hawaii, but also further evaluates regional BVAR models with linear combination priors.
ESSAY 3

Applying Bayesian Vector Autoregression to a Pseudo Regional Income and Product Account Model

3.1 Introduction

The past three decades has witnessed the wide use of regional econometric models in policy analysis and forecasting. Each state of the Union, as well as federal agencies (such as the Bureau of Economic Analysis) and private organizations (like DRI-WEFA Group), maintains econometric models of various degrees of aggregation and linkages with the national economy and neighboring regions. Their purpose of models range from policy impact evaluations to employment projection and tax revenue forecasting.

Nevertheless, data available at the state and county levels greatly limits the types of system structures feasible for regional models. With no expenditure-side gross state product (GSP) account data available, traditional income and product account theory driven macro models are precluded.\(^1\) A typical regional model uses data compiled by national and local statistics bureaus and model the economy via different blocks such as output, labor and capital demand, population and labor

\(^1\)The GSP data reported by the BEA are value added by industry and only available after a two-year lag.
supply, wages, prices and profits, and market shares (Treyz, 1993). However, the block structure is purely for ease of presentation, equations are typically estimated one at a time.

A less theory dependent methodology, vector autoregression (VAR), was introduced into regional econometric modelling in the early 1980s (Anderson, 1979). Unlike structural models where economic theory prescribes the specification and parameter values, in an unrestricted VAR, economic theory is used primarily to select variables and lag lengths. It is presumed that variables chosen are logically related. Nevertheless, the very specification of the VAR makes it vulnerable to multicollinearity and overparameterization problems. For a model with $m$ variables at lag length $k$, each equation of the VAR involves estimating $mk$ 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. In-sample regressions produce excellent fit, but out-of-sample forecasts are generally poor.

Litterman (1980, 1986) proposes a way to deal with the problem—Bayesian VAR (BVAR). Instead of eliminating insignificant variables and lags entirely, the BVAR approach assumes normal prior distributions for the coefficients of a VAR such that variables and lags of less importance have smaller standard deviations around prior means of zero. Numerous priors have been developed over the years, including the original Minnesota prior (Litterman, 1980), the Normal-Wishart prior (Kadiyala and Karlsson, 1993, 1997), and priors on linear combinations of parameters such as the sums of coefficients prior (Doan, Litterman, and Sims, 1984) and the dummy initial observation prior (Sims, 1993).

The BVAR methodology has demonstrated promising forecasting capabilities relative to traditional large-scale structural models (McNees, 1986; Litterman, 1986). In recent years, the technique has been gradually applied in regional modeling and forecasting. Existing efforts fall into two groups. The first group

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2The typical data used include income data from Bureau of Economic Analysis (BEA), employment and wage data from Bureau of Labor Statistics (BLS), population data from the Census Bureau, and other measures from the state and local governments.
employs exclusively the Minnesota prior and models collective economic series such
as the general price level, total industrial employment, total personal income and
overall tax revenue (Cargill and Morus, 1988; Dua and Ray, 1995; Crone and
McLaughlin, 1999). The second group focuses on more narrowly defined sectors of
the economy and models disaggregated variables. The most frequently modelled
sectors include industrial employment (Harris, 1990; Magura, 1990; Patridge and
Rickman, 1998; Puri and Soydemir, 2000; Rickman, 2001) and state tax revenues
(Whiteman, 1997). While the pure Minnesota prior is used most often, the second
group has made use of regional input-output information in forming prior means
and/or variances.

Despite these efforts, no regional BVAR model exists that a) fully accounts for
both the intra-actions within the region and the inter-actions of the region with
other economies; b) makes use of the latest developments in prior specifications
such as the sums of coefficients prior and the dummy initial observation prior. I
propose in this paper to set up a pseudo regional income and product account model
for the state of Hawaii, using BVAR blocks to mimic the different expenditure
categories. In particular, there is a Hawaii core block as well as blocks for private
and public consumption, construction investment, and external linkages.

The organization of the paper is as follows. Section 3.2 briefly reviews
the conceptual issues of BVAR together with prior specifications. Section 3.3
summarizes BVAR models at the regional level. Section 3.4 reviews the Hawaii
economy and existing econometric models for Hawaii. Section 3.5 proposes the
pseudo income and product account Hawaii BVAR forecasting model and reports
estimation results. Section 3.6 simulates the estimated BVAR forecasting model.
Section 3.7 evaluates the model's forecasting performance. Section 3.8 concludes.

3.2 The Bayesian VAR Methodology and Priors

Forecasting models in practice are often formulated as structural simultaneous
systems. For proper identification of individual equations, however, the correct
number of variables needs to be excluded from each equation. Cooley and
LeRoy (1985) argue that in practice, the exclusion restrictions used rarely have theoretical justifications. An alternative to identification is found in vector autoregression (VAR) models. Although the approach is “athoretical”, a VAR model approximates the reduced form of a structural system of simultaneous equations. Zellner (1979) shows that any linear structural model can be equivalently expressed as a vector autoregression moving average (VARMA) model and under certain conditions a VAR model is sufficient.

An unrestricted VAR(k) model in an $m \times 1$ vector $z_t$, as suggested by Sims (1980), can be written as,

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

(3.1)

where $k$, the order of the VAR, is assumed to be known a priori; $c$ is an $m \times 1$ vector of unknown constants; $\Phi_l$, $l = 1, 2, \ldots, k$, are $m \times m$ matrices of unknown parameters; $\epsilon_t$ is an $m \times 1$ vector of disturbances that is i.i.d. $(0, \Omega)$ and the initial values, $z_0, z_-1, \ldots, z_{-k+1}$ are taken as given.

The unrestricted VAR system in (3.1) suffers from severe lack of degrees of freedom. Each endogenous variable added to the system uses up $k$ degrees of freedom in every equation. The system quickly becomes overfit as the number of endogenous variables increases. Forecasts based on unrestricted Ordinary Least Squares (OLS) estimation of (3.1) for finite samples is not well determined. To solve the problem, Hoehn (1984) and Hoehn, Gruben, and Fomby (1984) offer statistical tests to eliminate insignificant variables and lags to reduce the amount of overparameterization and thereby improve forecasting accuracy, but their tests are time consuming. A more straight-forward solution is found in Litterman (1980) who makes use of Theil’s (1971) mixed regression technique and suggests a Bayesian method to estimate the coefficients for economic series with trends or persistent local levels. Instead of treating the underlying parameters as fixed values to be discovered by regression tools, Litterman treats coefficients as random quantities around prior mean values, where the tightness of the distribution around prior mean is determined via a set of hyperparameters. The main technical issues
thus involve the specification of prior distribution and the determination of the form of estimators.

### 3.2.1 The Minnesota Prior

The “Minnesota Prior” owes its name to its development at the Federal Reserve Bank of Minneapolis and the University of Minnesota (Litterman, 1980). Under the prior, individual elements of each lag coefficient matrix $\Phi_l$ in (3.1) are independently and normally distributed random variables with the mean of the coefficient matrix on the first lag, $\Phi_1$, equal to an identity matrix and the mean of the coefficient matrices on other lags, $\Phi_l$, $l = 2, 3, \ldots, k$, equal to zero.\(^3\) If these restrictions were exact, each variable in (3.1) would follow a random walk process, possibly with nonzero drift. In the BVAR setting, however, the random walk assumption does not have to be imposed exactly, but is specified as inexact prior with the standard deviation, $S(i,j,l)$, of the $ij$-th element in the $l$-th lag coefficient matrix $\Phi_l$ given by,

$$
S(i,j,l) = \begin{cases} 
\lambda_1/l^{\lambda_3} & \text{if } i = j, \\
\sigma_1\lambda_1\lambda_2/\sigma_j l^{\lambda_3} & \text{if } i \neq j.
\end{cases}
$$

(3.2)

In equation (3.2), $\lambda_1$ is the overall tightness parameter. It is the prior standard deviation of the $ii$-th element of $\Phi_1$ and controls how closely the random walk prior is imposed. As $\lambda_1$ approaches zero, the diagonal elements of $\Phi_1$ approach one and all other coefficients shrink to zero, i.e., a stronger random walk assumption. Because own lags tend to be more important in explaining the dependent variable than lags of other variables, coefficients on lags of other variables are assigned a relatively smaller variance around the prior mean of zero. This relative tightness is controlled by choosing a value for $\lambda_2$ that is between zero and one ($0 < \lambda_2 \leq 1$). A smaller value for $\lambda_2$ has the effect of shrinking the off-diagonal elements of $\Phi_l$ towards zero. If $\lambda_2$ is set to unity, lags of other variables are treated the same.

\(^3\)This is equivalent as saying that the prior mean for the first lag of the dependent variable is one and the prior mean for everything else is zero.
as lags of the dependent variable. It is also assumed that the impact of a lagged variable decreases as the lag length increases. This is captured by the parameter $\lambda_3$. As $\lambda_3$ increases, the prior variance of the coefficients on higher order lags shrinks toward zero. If $\lambda_3$ is set to one, the rate of decay is harmonic. Finally, the prior standard deviations are scaled by the ratio $(\sigma_i/\sigma_j)$ to account for the different units of measurement for variables in the system. In practice, $\sigma_i$ is usually set to the residual standard deviation of a univariate autoregression on equation $i$. The constant term $c$ in (3.1) has different inexact prior specifications in the literature. The most commonly seen is a prior mean of zero with standard deviation $\sigma_1\lambda_4$. As $\lambda_4$ decreases, the constant shrinks to zero.

To illustrate the Minnesota prior, suppose we have a two-variable system ($m = 2$) with a lag length of 2 ($k = 2$). The Minnesota prior has prior means given by,

$$
\bar{b}_1 = \begin{pmatrix} 0 \\ 1 \\ 0 \\ 0 \\ 0 \end{pmatrix},
$$

(3.3)

$$
\bar{b}_2 = \begin{pmatrix} 0 \\ 0 \\ 1 \\ 0 \\ 0 \end{pmatrix},
$$

(3.4)

and prior variances,

$$
\overline{G}_1 = \begin{pmatrix}
(\sigma_1\lambda_4)^2 & 0 & 0 & 0 & 0 \\
0 & (\lambda_1)^2 & 0 & 0 & 0 \\
0 & 0 & (\sigma_1\lambda_1\lambda_2/\sigma_2)^2 & 0 & 0 \\
0 & 0 & 0 & (\lambda_1/2\lambda_3)^2 & 0 \\
0 & 0 & 0 & 0 & [\sigma_1\lambda_1\lambda_2/(2\lambda_3\sigma_2)]^2
\end{pmatrix},
$$

(3.5)

---

4When monthly data are used to fit a VAR system, a special decay factor is used to approximate a harmonic decay pattern at a quarterly frequency. See Robertson and Tallman (1999).
where columns of the matrices correspond to $c, z_{1,t-1}, z_{2,t-1}, z_{1,t-2}$ and $z_{2,t-2}$ respectively.

To estimate the coefficients, note first that the OLS estimator of coefficients in the $i$-th equation of the VAR system in (3.1) is,

$$\hat{b}_i^{OLS} = (X'X)^{-1}X'z_i, \quad i = 1, 2, \ldots, m,$$

where $z_i$ is a $T \times 1$ vector with $n$-th element $(z_{i,n})$ and $X$ is a $T \times (mk + 1)$ matrix with $n$-th row $(1 \quad z_{1,n-1} \quad \cdots \quad z_{m,n-1} \quad z_{1,n-2} \quad \cdots \quad z_{m,n-2} \quad z_{1,n-k} \quad \cdots \quad z_{m,n-k})$. The BVAR estimator is obtained via a Theil's (1971) mixed regression and the mean of the posterior distribution is given by,

$$\hat{b}_i^{BVAR} = (\overline{G}_i^{-1} + \sigma_i^{-2}X'X)^{-1}(\overline{G}_i^{-1}\overline{b}_i + \sigma_i^{-2}X'z_i).$$

In summary, the Bayesian technique allows a model builder to incorporate prior statistical and economic knowledge in a scientific way to specify the best guess for all parameter values. In addition, the model builder specifies confidence in the values of the coefficients. The extent to which data are allowed to revise the modeler's estimate of a particular coefficient depends on the modeler's confidence in the guess. If he is highly confident, the historical patterns of the data receive low weight and vice versa. The prior variance or standard deviation of the coefficients measures how confident the modeler is about his prior guess. A small prior variance indicates a high confidence that the estimated coefficients closely match the best guess. A large variance implies that the estimated coefficients might vary significantly from the modeler's initial guess.
3.2.2 The Normal-Wishart Prior

The BVAR using a Minnesota prior as originally developed by Litterman (1980) is estimated one equation at a time. Litterman (1980) shows that this reduces the computational burden by the square of the number of variables, \( km^2 \). Nevertheless, single-equation estimation is valid for an unrestricted covariance matrix, \( \Omega \), only when the same independent variables appear on the right-hand side of each equation and the prior for each variable has the same form. It is clear that the Minnesota prior violates the second criterion because the parameters controlling the prior variance on other lagged variables \((\lambda_2)\) is different from one. In practice, single equation estimation precedes under the assumption that the residual covariance matrix \( D \) is close to diagonal. Litterman (1980) acknowledges that "there could be a gain in efficiency by estimating all equations together...the departures from full efficiency will depend on how far from diagonal is the covariance matrix of residuals from different equations and the relative strength of asymmetric prior information to data evidence".\(^5\)

Recent work relaxes the assumption of a diagonal covariance matrix by using the Normal-Wishart prior (Kadiyala and Karlsson, 1993, 1997). Under the Normal-Wishart prior, the prior distribution of the regression coefficients conditional on the error covariance matrix \( \Omega \) is Normal, and the prior distribution of \( \Omega \) is inverse Wishart. The coefficient estimator (i.e., the mean of the posterior distribution) is,

\[
\hat{B} = (H^{-1} + X'X)^{-1}(H^{-1}\bar{B} + X'z),
\]

where \( \bar{B} \) is the prior mean of the coefficient matrix, and \( H \) is the \((mk + 1) \times (mk + 1)\) diagonal, positive-definite prior covariance matrix. The covariance matrix estimator is,

\[
\hat{\Omega} = T^{-1}(z'z - \hat{B}'(H^{-1} + X'X)\hat{B} + \bar{B}'H^{-1}\bar{B} + \bar{S}),
\]

where \( \bar{S} \) is a \( m \times m \) diagonal scale matrix in the prior inverse-Wishart distribution.

for $\Omega$.

We again use a two-variable ($m = 2$), two-lag ($k = 2$) system to illustrate the Normal-Wishart prior. The prior information is given by,

$$
\bar{B} = \begin{pmatrix} 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{pmatrix},
$$

(3.11)

$$
\bar{S} = \begin{pmatrix} (\sigma_1/\lambda_0)^2 & 0 \\ 0 & (\sigma_2/\lambda_0)^2 \end{pmatrix},
$$

(3.12)

$$
\bar{H} = \begin{pmatrix} (\lambda_0 \lambda_4)^2 & 0 & 0 & 0 & 0 \\ 0 & (\lambda_0 \lambda_1/\sigma_1)^2 & 0 & 0 & 0 \\ 0 & 0 & (\lambda_0 \lambda_1/\sigma_2)^2 & 0 & 0 \\ 0 & 0 & 0 & [\lambda_0 \lambda_1/(2 \lambda^3 \sigma_1)]^2 & 0 \\ 0 & 0 & 0 & 0 & [\lambda_0 \lambda_1/(2 \lambda^3 \sigma_2)]^2 \end{pmatrix},
$$

(3.13)

where parameter $\lambda_0$ governs the overall tightness of the prior on $\Omega$.

It is easy to see the relation between the Minnesota prior and the Normal-Wishart prior. The Normal-Wishart prior involves a Kronecker product of $\bar{S}$ and $\bar{H}$ which results in an $m(mk + 1) \times m(mk + 1)$ scale matrix whose elements are exactly the coefficient prior variances under the Minnesota prior with $\lambda_2 = 1$. The restriction applies because the Normal-Wishart prior prohibits lags of the dependent variable from being treated differently from lags of other variables in an equation. Alternatively, the restriction on $\lambda_2$ is the price paid to relax the stringent assumption that residual covariance matrix $\Omega$ is diagonal in the Minnesota prior while retaining the random-walk property.
3.2.3 Priors on Linear Combinations of the Coefficients

Another strain of literature seeks to modify the Minnesota prior in the direction of linear combinations of the coefficients in equation (3.1). It introduces nonzero off-diagonal terms into the prior covariance of individual coefficients and is thus more easily implemented from the dual side by mixing a set of dummy observations into the data set. Sims and Zha (1998) show that the Minnesota prior can also be implemented by adding a set of \( k - 1 \) dummy observations to the matrix used to estimate the \( i \)-th equation.\(^6\) The only difference is that the "dummy observations" for the Minnesota prior are equation-specific, whereas priors discussed below are true, system-wide dummy observations.

**Sums of Coefficients Prior**

In the literature, there are two priors on dummy observations. The first, known as the *sums of coefficients* prior, is introduced in Doan, Litterman, and Sims (1984) and expresses a prior belief that when data contain stochastic trends (unit roots), a VAR in first differences is appropriate. The *sums of coefficients* prior implicitly assumes that coefficients on lags of the dependent variable in each equation sum up to one while coefficients on lags of other variables sum up to zero. Rewrite equation (3.1) in error correction form,

\[
\Delta z_t = -\Pi z_{t-1} + \Gamma_1 \Delta z_{t-1} + \cdots + \Gamma_{k-1} \Delta z_{t-k+1} + c + \epsilon_t,
\]

where \( \Pi = I_m - \sum_{i=1}^k \Phi_i, \Gamma_i = -\sum_{j=i+1}^k \Phi_j, i = 1, \ldots, k - 1. \) Note that when \( \sum_{i=1}^k \Phi_i = I_m, -\Pi z_{t-1} \) drop out of equation (3.14) and the whole system is specified in first differences. In practice, the *sums of coefficients* prior is implemented by adding to the data set \( m \) dummy observations, in which \( X_{t-i} \) is set to zero for \( i = 1, \ldots, k, \) except for \( X_{t-1}^j, i = 1, \ldots, k, \) which corresponds to the dependent variable and is set to \( \bar{z}_j^0, \) the mean of the \( k \) presample values for variable \( z_j. \) Dummies corresponding to the constant vector are set to zero.

\(^6\) As is typical in a prime-dual problem, the scale factors on dummy observations are precisely the reciprocal of those on prior covariance matrix.
To illustrate the sums of coefficients prior, suppose we have a two-variable \((m = 2)\), two-lag \((k = 2)\) system the VAR specification for which is,

\[
\begin{pmatrix}
  z_{1,t} \\
  z_{2,t}
\end{pmatrix} = \begin{pmatrix} c_1 & c_2 \end{pmatrix} + \begin{pmatrix} z_{1,t-1} & z_{2,t-1} \end{pmatrix} \begin{pmatrix} \phi_{1,1}^1 & \phi_{1,1}^2 \\
  \phi_{2,1}^1 & \phi_{2,1}^2 \end{pmatrix} + \begin{pmatrix} z_{1,t-2} & z_{2,t-2} \end{pmatrix} \begin{pmatrix} \phi_{1,2}^1 & \phi_{1,2}^2 \\
  \phi_{2,2}^1 & \phi_{2,2}^2 \end{pmatrix} + \begin{pmatrix} \epsilon_{1,t} & \epsilon_{2,t} \end{pmatrix}
\]

(3.15)

where \(\phi_{j,t}^l\) is the coefficient on the \(l\)-th lag of \(j\)-th variable in the \(i\)-th equation and \(z_{i,t}\) is the \(T \times 1\) vector of sample observations \((i = 1, 2)\). Imposing the sums of coefficients prior involves stacking to the sample matrix two dummy observations,

\[
\begin{pmatrix}
  z_1^0 \\
  0 \\
  0 \\
  z_2^0
\end{pmatrix},
\]

(3.16)

for the dependent variables and,

\[
\begin{pmatrix}
  0 & z_1^0 & 0 & z_1^0 & 0 \\
  0 & 0 & z_2^0 & 0 & z_2^0
\end{pmatrix},
\]

(3.17)

for the independent variables. A weight of \(\lambda_5 \geq 0\) is attached to these dummy observations. This implies that the following equalities hold,

\[
\begin{pmatrix}
  \lambda_5 z_1^0 & 0 \\
  0 & \lambda_5 z_2^0
\end{pmatrix} = \begin{pmatrix} 0 \\
  0 \end{pmatrix} \begin{pmatrix} c_1 & c_2 \end{pmatrix} + \begin{pmatrix} \lambda_5 z_1^0 & 0 \\
  0 & \lambda_5 z_2^0 \end{pmatrix} \begin{pmatrix} \phi_{1,1}^1 & \phi_{1,1}^2 \\
  \phi_{2,1}^1 & \phi_{2,1}^2 \end{pmatrix} + \begin{pmatrix} \lambda_5 z_1^0 & 0 \\
  0 & \lambda_5 z_2^0 \end{pmatrix} \begin{pmatrix} \phi_{1,2}^1 & \phi_{1,2}^2 \\
  \phi_{2,2}^1 & \phi_{2,2}^2 \end{pmatrix}
\]

(3.18)
Expanding equation (3.18) yields four conditions,

\[
\begin{align*}
\lambda_5 z_1^0 = \lambda_5 z_1^0 \phi_{1,1}^1 + \lambda_5 z_1^0 \phi_{1,2}^1; \\
0 = \lambda_5 z_1^0 \phi_{1,1}^2 + \lambda_5 z_1^0 \phi_{1,2}^2; \\
0 = \lambda_5 z_2^0 \phi_{2,1}^1 + \lambda_5 z_2^0 \phi_{2,2}^1; \\
\lambda_5 z_2^0 = \lambda_5 z_2^0 \phi_{2,1}^2 + \lambda_5 z_2^0 \phi_{2,2}^2. 
\end{align*}
\] (3.19)

Under the conditions that \(\lambda_5 z_1^0 \neq 0\) and \(\lambda_5 z_2^0 \neq 0\), we have

\[
\begin{align*}
1 &= \phi_{1,1}^1 + \phi_{1,2}^1; \\
0 &= \phi_{1,1}^2 + \phi_{1,2}^2; \\
0 &= \phi_{2,1}^1 + \phi_{2,2}^1; \\
1 &= \phi_{2,1}^2 + \phi_{2,2}^2. 
\end{align*}
\] (3.20)

From equation (3.14), the \(\Pi\) matrix in this case is

\[
\Pi = I_2 - \sum_{i=1}^2 \Phi_i = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} - \begin{pmatrix} \phi_{1,1}^1 & \phi_{1,1}^1 \\ \phi_{1,1}^2 & \phi_{1,2}^2 \end{pmatrix} - \begin{pmatrix} \phi_{1,2}^1 & \phi_{1,2}^1 \\ \phi_{2,1}^2 & \phi_{2,2}^2 \end{pmatrix} = 0
\] (3.21)

Therefore, the sums of coefficients prior implies that a VAR system in first differences is appropriate. As \(\lambda_5\) increases, more weight is put on the prior and the it is increasingly satisfied. In the limiting case where \(\lambda_5 \to \infty\), there are as many unit roots as variables and there is no cointegration. Since the constant term is excluded from prior specification, nonzero constant terms and thereby linearly trending drifts are allowed even in the limit.

**Dummy Initial Observation Prior**

It is sometimes reasonable to assume that there are fewer stochastic trends in the VAR system (3.1) than there are variables, i.e., there exist stable cointegrating relations among the trending series. To account for this, Sims (1993) adds an additional dummy observation in which all values of all variables are set to the
corresponding presample averages \((\bar{z}_i^0, i = 1, \ldots, m)\) and the value of constant to 1. The prior, known in the literature as the *dummy initial observation* prior, introduces correlation among coefficients on different variables in a given equation including the constant term. It allows for cointegration while maintaining the unit-root nonstationarity in all variables.

For the simple case of two variables and two lags in equation (3.15), the *dummy initial observation* prior in the \(i\)-th equation is \((\bar{z}_i^0)\) for the dependent variable and \((1 \quad \bar{z}_1^0 \quad \bar{z}_2^0 \quad \bar{z}_1^0 \quad \bar{z}_2^0)\) for the independent variables. A scale factor of \(\lambda_6 \geq 0\) is assigned to this dummy observation. The following equality holds under the *dummy initial observation* prior,

\[
\begin{pmatrix}
\lambda_6 \bar{z}_1^0 & \lambda_6 \bar{z}_2^0
\end{pmatrix} = \begin{pmatrix} 1 \\ \lambda_6 \end{pmatrix} \begin{pmatrix} c_1 \\ c_2 \end{pmatrix} + \begin{pmatrix}
\phi_{1,1}^0 & \phi_{1,2}^0 \\
\phi_{2,1}^0 & \phi_{2,2}^0
\end{pmatrix} \begin{pmatrix}
\lambda_6 \bar{z}_1^0 & \lambda_6 \bar{z}_2^0 \\
\phi_{1,1}^0 & \phi_{1,2}^0
\end{pmatrix} + \begin{pmatrix}
\phi_{1,2}^0 & \phi_{1,2}^0 \\
\phi_{2,2}^0 & \phi_{2,2}^0
\end{pmatrix} \begin{pmatrix}
\lambda_6 \bar{z}_1^0 & \lambda_6 \bar{z}_2^0 \\
\phi_{1,2}^0 & \phi_{2,2}^0
\end{pmatrix}.
\]

(3.22)

Expanding equation (3.22) yields,

\[
\begin{align*}
\lambda_6 \bar{z}_1^0 &= c_1 + \lambda_6 \bar{z}_1^0 \phi_{1,1}^1 + \lambda_6 \bar{z}_2^0 \phi_{2,1}^1 + \lambda_6 \bar{z}_1^0 \phi_{1,2}^1 + \lambda_6 \bar{z}_2^0 \phi_{2,1}^2; \\
\lambda_6 \bar{z}_2^0 &= c_2 + \lambda_6 \bar{z}_1^0 \phi_{1,1}^2 + \lambda_6 \bar{z}_2^0 \phi_{2,1}^2 + \lambda_6 \bar{z}_1^0 \phi_{1,2}^2 + \lambda_6 \bar{z}_2^0 \phi_{2,2}^2.
\end{align*}
\]

(3.23)

Under the condition that \(\lambda_6 \neq 0\), we have

\[
\begin{pmatrix}
\bar{z}_1^0 \\
\bar{z}_2^0
\end{pmatrix} = \frac{1}{\lambda_6} \begin{pmatrix} c_1 \\ c_2 \end{pmatrix} + \begin{pmatrix}
\phi_{1,1}^1 + \phi_{1,2}^1 & \phi_{1,1}^1 + \phi_{1,2}^1 \\
\phi_{2,1}^1 + \phi_{1,2}^2 & \phi_{2,1}^1 + \phi_{2,2}^2
\end{pmatrix} \begin{pmatrix}
\bar{z}_1^0 \\
\bar{z}_2^0
\end{pmatrix}.
\]

(3.24)

or,

\[
\begin{pmatrix}
1 - (\phi_{1,1}^1 + \phi_{1,2}^1) \\
- (\phi_{2,1}^1 + \phi_{2,2}^2)
\end{pmatrix} \begin{pmatrix} c_1 \\ c_2 \end{pmatrix} = \frac{1}{\lambda_6} \begin{pmatrix} c_1 \\ c_2 \end{pmatrix}.
\]

(3.25)
As \( \lambda_6 \to \infty \), the right hand side of equation (3.25) converges to zero, so that

\[
\begin{pmatrix}
1 - (\phi_{1,1}^1 + \phi_{1,2}^1) & - (\phi_{1,1}^1 + \phi_{2,2}^1) \\
-(\phi_{1,1}^2 + \phi_{1,2}^2) & 1 - (\phi_{2,1}^2 + \phi_{2,2}^2)
\end{pmatrix}
\begin{pmatrix}
z_1^0 \\
z_2^0
\end{pmatrix} =
\begin{pmatrix}
0 \\
0
\end{pmatrix}.
\] (3.26)

Since \( z_1^0 \) and \( z_2^0 \) are non-zero values,

\[
1 - (\phi_{1,1}^1 + \phi_{1,2}^1) = -k(\phi_{1,1}^2 + \phi_{1,2}^2),
\]

\[
-(\phi_{1,1}^2 + \phi_{1,2}^2) = k[1 - (\phi_{2,1}^2 + \phi_{2,2}^2)],
\] (3.27)

where \( k \) is a nonzero constant. From equation (3.14), the \( \Pi \) matrix is

\[
\Pi = I_2 - \sum_{i=1}^{2} \Phi_i =
\begin{pmatrix}
1 & 0 \\
0 & 1
\end{pmatrix} -
\begin{pmatrix}
\phi_{1,1}^1 & \phi_{1,1}^2 \\
\phi_{1,1}^2 & \phi_{2,1}^2
\end{pmatrix} -
\begin{pmatrix}
\phi_{1,2}^1 & \phi_{1,2}^2 \\
\phi_{2,1}^2 & \phi_{2,2}^2
\end{pmatrix}
\]

\[
= \begin{pmatrix}
1 - (\phi_{1,1}^1 + \phi_{1,2}^1) & -(\phi_{1,1}^2 + \phi_{1,2}^2) \\
-(\phi_{1,1}^2 + \phi_{1,2}^2) & 1 - (\phi_{2,1}^2 + \phi_{2,2}^2)
\end{pmatrix}.
\] (3.28)

It is clear that when conditions in (3.27) holds, the rank of \( \Pi \) is one, i.e., there is a single cointegrating vector. Therefore, in the limiting case where \( \lambda_6 \to \infty \), the dummy initial observation prior implies that more weight is put on a VAR where all series share the same stochastic trend and the intercept approaches zero. The sums of coefficients and dummy initial observation priors, when imposed together, favor unit roots with a single cointegrating relationship.

### 3.3 Regional Economic Models and BVAR Methodology

Structural and time series methods have both been employed in regional econometric modelling exercises. Structural models are loosely defined as systems of equations that specify behavioral, technological, institutional, definitional and equilibrium relations among a given set of economic variables. Typical in these models, variables are categorized into "endogenous" (determined within the
system) and "exogenous" (determined outside of the system) with endogenous variables linked to exogenous variables through behavioral or non-behavioral equations. Structural regional models have traditionally followed the Keynesian macroeconomic framework of aggregate demand analysis, modified to deal with region specific issues such as migration. Examples of regional structural models include multi-equation Keynesian models, input-output models, economic base models, and a variety of demographic models.

Nevertheless, regional structural models suffer from two drawbacks. First, data available at subnational levels greatly limits the applicability of Keynesian framework. Traditional income and product account theory driven macro models are largely precluded because no expenditure-side GSP data exists at sub-national levels. Second, structural models are generally large in size, difficult to maintain, and costly to update. Newly available information does not get incorporated into the model on a timely basis.

The BVAR methodology introduced in Section 3.2 offers an effective alternative. It is designed primarily to forecast and relies explicitly on forecast performance in picking priors. The most often used criteria include Root Mean Squared Errors (RMSE), Absolute Mean Squared Errors (AMSE) and Theil's U statistic. There is no subjective adjustment involved and new information is easily integrated by re-picking the priors. McNees (1986) shows that BVAR models forecast at least as good, if not better than, several well-known structural models. Nevertheless, the BVAR methodology is subject to size limit. It is rare to see models with more than 15 variables. As such, a single BVAR model can forecast either aggregate economic indicators or sector details, but not both. The following sections review existing regional BVAR models according to level of aggregation.

3.3.1 BVAR Models at the Aggregate Level

BVAR models at the aggregate level have been used on small collections of economic indicators. Examples of this category include a BVAR for the Nevada economy (Cargill and Morus, 1988), for the state of Connecticut (Dua and Ray,
1995), for the city and metropolitan area of Philadelphia (Crone and McLaughlin, 1999), and for Southern California (Puri and Soydemir, 2000). These models typically contain three to four regional economic indicators and a number of driver series from the nation and/or neighboring regions. For instance, the Nevada BVAR forecasting model (Cargill and Morus, 1988) contains eight variables. The first three variables are Nevada specific, including total industrial employment, total taxable sales and gross gaming revenues. The fourth variable, California civilian employment, supposedly captures California’s influence on Nevada due to geographical proximity and economic interrelatedness. Another four national variables capture economic impacts on Nevada from the rest of the nation: real gross national product (GNP), the annualized rate of inflation measured by the GNP deflator, total civilian employment, and the 6-month commercial paper rate.

BVAR models in this category invariably use the Minnesota prior. The prior mean on the first lag of the dependent variable is set to one and the prior means on other variables and lags are set to zeros. Prior variances are determined by criteria such as RMSE or Theil’s (1971) U statistic. It is not uncommon to employ Litterman’s circle-star structure to shrink the search range. Star (national) variables affect both star and circle (regional) variables while circle (regional) variables influence primarily other circle (regional) variables. In Crone and McLaughlin (1999), the block recursive structure is extended to the metropolitan area against the city such that metro-area variables influence city variables but not vice versa.

3.3.2 BVAR Models at the Disaggregate Level

For BVAR models at the disaggregate level, the most frequently modelled area is industrial employment (Harris, 1990; Magura, 1990; Patridge and Rickman, 1998; and Rickman, 2001). A small number of national economic indicators are sometimes used as drivers. For instance, Harris (1990) includes the U.S. inflation rate and GNP and 3-month Treasury bill rate. A typical model covers one-digit level industries like construction; manufacturing; transportation, communication,
public utilities; trade; finance, insurance, real estate; service; and government. Some sectors may be further decomposed into two-digit level industries such as total trade into wholesale and retail trade.

While the Minnesota prior is the most common, Patridge and Rickman (1998) make use of regional input-output information in forming prior means and variances. They employ the IMPLAN regional input-output coefficients for Georgia in a BVAR forecasting model. The input-output coefficients are used to specify both the prior variances of a model with Minnesota prior means and the prior means of a model with Minnesota prior variances. Patridge and Rickman (1998) show that inclusion of the interindustry relations helps to forecast the long-run trends of the economy as well as the turning points.

3.3.3 The Multi-layer BVAR Model with Blocks

Due to size limitations, a tradeoff exists in BVAR models between accounting for the inter-regional and intra-regional relations. In the literature, one solution is found in constructing BVAR models in blocks. Whiteman (1997) establishes a BVAR forecasting system for Iowa state tax revenues. The model is composed of four individual BVAR blocks. The first three blocks focus on general economic conditions, describing the nominal personal income, real personal income, and employment. In particular, the nominal personal income block includes total Iowa personal income, wage and salary disbursements, property income, transfers, and farm income, together with their national counterparts. The real income block comprises the same ten variables, deflated by Gross Domestic Product (GDP) deflator. The employment block includes total Iowa nonagricultural employment, population, and employment in durable and nondurable goods manufacturing, services, wholesale and retail trade sectors, together with the corresponding national variables. The last block is devoted to state tax revenues and consists of only two variables, general revenue receipts and total Iowa personal income.

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7 According to North American Standard Industrial Classification (NASIC) codes.
8 IMPLAN is a nonsurvey, industry-based input-output model that is available for any state- or county-based region in the United States.
through which the block is linked to the previous three. Whiteman (1997) shows that the BVAR block recursive structure has promising forecasting performance.

Unfortunately, there is little reason to believe that the series included in Whiteman (1997) are either comprehensive or representative. More importantly, the model lacks a systematic structure. The grouping of series into different BVAR blocks follows regional data reporting convention. Whiteman acknowledges that there is no widely embraced structure for regional economic modeling and that the framework employed in his model, the so-called export-base notion, is just a notion, rather than a fully established theory.

At the national level, however, there has long been BVAR systems that mimic the income and product accounts structure. The U.S. BVAR forecasting model maintained by the Federal Reserve Bank at Minneapolis (Amirizadeh, 1985) consists of eight blocks: core, price, production, labor, government, consumption, financial markets, and international trade. Each block contains no more than 13 variables. The system is block recursive in that key economic indicators are determined within the core block and feed into other blocks. In particular, the core block includes real GNP, the GNP deflator, 3-month treasury bill rate (T-bill), S & P 500 index, $M_1$ money supply, trade-weighted value of dollar, total nonfinancial debt (Debt), and the change in business inventories. Forecasts of these variables are then fed into the remaining seven BVAR blocks to form other forecasts. For instance, the GNP deflator, T-bill, S & P 500 index, $M_1$, and Debt are used in the financial markets block to predict monetary base, $M_2$ money supply, federal funds rate, 10-year bond yields and the consumer price index (CPI). Note that some blocks contain variables not only from the core, but also from other blocks. In this sense, these blocks are secondary in the recursive structure.

In the literature, no regional BVAR system exists that uses the income and product account structure to accommodate the interactions both between the region and external drivers and among the various sectors within the region. This paper thus represents the first attempt to construct such a forecasting system.

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9For a detailed account of the rest interactions, see Amirizadeh (1985).
The newly developed *sums of coefficient* prior and the *dummy initial observation* prior are employed to account for possible cointegrating relations. The model is developed for the state of Hawaii because of the availability of excise tax base data useful in mimicking the expenditure flows in various sectors.

### 3.4 The Hawaii Economy and Existing Econometric Models

#### 3.4.1 The Hawaii Economy

The State of Hawaii experienced rapid economic growth over the past 25 years. Gross State Product (GSP) increased from $9.4 billion in 1977 to $42.4 billion in 2000. This 6.5 percent average annual growth rate is comparable to the 6.9 percent growth in U.S. Gross Domestic Product (GDP) over the same period. Even after adjusting for inflation, Hawaii’s GSP grew at a healthy rate, averaging 2.1 percent annually from 1977 to 2000.\(^{10}\) Over the same period, Hawaii’s resident population grew at an average rate of 1.2 percent each year, rising from 915,749 in 1977 to 1,211,537 in 2000. This, taken together with the GSP growth, yields a per capita GSP that grew from $10,265 in 1977 to $34,997 in 2000 with an average growth rate of 5.3 percent.

Personal Income in Hawaii also increased considerably over the same period, rising from $7.7 billion in 1977 to $33.8 billion in 2000. This represents an average growth rate of 6.4 percent per year. When adjusted for inflation, personal income expanded at a rate of 2 percent per annum. Table 3.1 lists the average annual growth rate of the demographic and economic indicators for selected periods.

The structure of Hawaii’s Economy changed as it grew. In 1977, the total goods producing sector—comprised of agriculture; construction, mining; and manufacturing—represented 13.9 percent of GSP while the broadly defined services sector—including government; transportation and utilities; retail and wholesale

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\(^{10}\)The Honolulu Consumer Price Index (CPI) is used to calculate the inflation rate, which averages 4.4 percent from 1977 to 2000.
Table 3.1: Selected Key Economic Indicators of Hawaii: 1977-2000

<table>
<thead>
<tr>
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</tr>
</thead>
<tbody>
<tr>
<td>Population</td>
<td>1.3</td>
<td>1.1</td>
<td>1.2</td>
<td>0.6</td>
<td>0.5</td>
</tr>
<tr>
<td>Personal income</td>
<td>1.5</td>
<td>3.7</td>
<td>1.8</td>
<td>-0.1</td>
<td>1.5</td>
</tr>
<tr>
<td>Per capita income</td>
<td>0.2</td>
<td>2.6</td>
<td>0.6</td>
<td>-0.7</td>
<td>1.0</td>
</tr>
<tr>
<td>GSP</td>
<td>1.1</td>
<td>4.4</td>
<td>2.5</td>
<td>-0.8</td>
<td>1.9</td>
</tr>
<tr>
<td>Per capita GSP</td>
<td>-0.2</td>
<td>3.3</td>
<td>1.3</td>
<td>-1.4</td>
<td>1.4</td>
</tr>
<tr>
<td>Employment</td>
<td>2.4</td>
<td>1.9</td>
<td>3.2</td>
<td>-0.4</td>
<td>0.8</td>
</tr>
</tbody>
</table>


trade; finance, insurance, real estate; and other services—accounted for the remaining 86.1 percent. In 2000, the goods producing sector's in GSP declined to 8.8 percent and the broadly defined services sector's share increased to 91.8 percent. Table 3.2 lists the decomposition of GSP by industry for selected years.

Table 3.2: Hawaii Gross State Product by Industry: 1977–2000

<table>
<thead>
<tr>
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<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Total</td>
<td>100.0</td>
<td>100.0</td>
<td>100.0</td>
<td>100.0</td>
<td>100.0</td>
<td>100.0</td>
</tr>
<tr>
<td>Private Industries</td>
<td>72.3</td>
<td>74.5</td>
<td>75.3</td>
<td>79.2</td>
<td>78.6</td>
<td>78.6</td>
</tr>
<tr>
<td>Agriculture, Forestry, and Fisheries</td>
<td>2.3</td>
<td>2.2</td>
<td>2.0</td>
<td>1.6</td>
<td>1.3</td>
<td>1.3</td>
</tr>
<tr>
<td>Construction and Mining</td>
<td>6.1</td>
<td>5.7</td>
<td>4.9</td>
<td>6.6</td>
<td>4.6</td>
<td>4.4</td>
</tr>
<tr>
<td>Manufacturing</td>
<td>5.5</td>
<td>4.8</td>
<td>4.3</td>
<td>3.7</td>
<td>3.0</td>
<td>3.1</td>
</tr>
<tr>
<td>Transportation and Utilities</td>
<td>10.0</td>
<td>9.4</td>
<td>9.7</td>
<td>9.7</td>
<td>10.4</td>
<td>10.1</td>
</tr>
<tr>
<td>Wholesale and Retail Trade</td>
<td>15.4</td>
<td>15.0</td>
<td>14.5</td>
<td>14.6</td>
<td>15.1</td>
<td>14.8</td>
</tr>
<tr>
<td>Finance, Insurance, and Real Estate</td>
<td>16.9</td>
<td>20.6</td>
<td>21.7</td>
<td>22.7</td>
<td>22.3</td>
<td>22.5</td>
</tr>
<tr>
<td>Services</td>
<td>15.9</td>
<td>16.8</td>
<td>18.3</td>
<td>20.4</td>
<td>21.8</td>
<td>22.5</td>
</tr>
<tr>
<td>Government</td>
<td>27.7</td>
<td>25.5</td>
<td>24.7</td>
<td>20.8</td>
<td>21.4</td>
<td>21.4</td>
</tr>
</tbody>
</table>


On the employment side, total wage and salary jobs increased from 370,008 jobs in 1977 to 560,988 jobs in 2001, for an average annual growth rate of 1.75 percent. The relative growth across industries was not even, however. Jobs in the goods sector dropped from 53,500 in 1977 to 48,954 in 2001, a net loss of 4,546
jobs. Among these, the agriculture industry lost 3,196 jobs and the manufacturing industry 5,300 jobs while the construction and mining industry actually gained 3,950 jobs. Major job growth occurred in the service-related industries, ranging from 27% in the finance, insurance, real estate industry to 220% in the narrowly defined services industry (see table 3.3).

Table 3.3: Hawaii Employment by Industry: 1977–2001

<table>
<thead>
<tr>
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<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Wage and Salary Jobs</td>
<td>370,008</td>
<td>416,292</td>
<td>448,700</td>
<td>548,696</td>
<td>538,108</td>
<td>560,988</td>
</tr>
<tr>
<td>Total Non-agriculture</td>
<td>359,425</td>
<td>404,792</td>
<td>438,558</td>
<td>539,142</td>
<td>530,717</td>
<td>553,600</td>
</tr>
<tr>
<td>Agriculture</td>
<td>10,583</td>
<td>11,500</td>
<td>10,142</td>
<td>9,554</td>
<td>7,392</td>
<td>7,387</td>
</tr>
<tr>
<td>Construction and Mining</td>
<td>19,742</td>
<td>21,883</td>
<td>18,633</td>
<td>33,525</td>
<td>23,658</td>
<td>23,692</td>
</tr>
<tr>
<td>Manufacturing</td>
<td>23,175</td>
<td>22,992</td>
<td>22,050</td>
<td>20,458</td>
<td>16,683</td>
<td>17,875</td>
</tr>
<tr>
<td>Transportation and Utilities</td>
<td>28,200</td>
<td>31,867</td>
<td>34,200</td>
<td>43,308</td>
<td>41,033</td>
<td>42,075</td>
</tr>
<tr>
<td>Wholesale and Retail Trade</td>
<td>92,200</td>
<td>105,442</td>
<td>117,950</td>
<td>136,442</td>
<td>135,225</td>
<td>136,250</td>
</tr>
<tr>
<td>FIRE*</td>
<td>25,650</td>
<td>31,725</td>
<td>33,150</td>
<td>37,383</td>
<td>36,892</td>
<td>32,692</td>
</tr>
<tr>
<td>Services</td>
<td>84,750</td>
<td>101,908</td>
<td>118,725</td>
<td>159,108</td>
<td>166,650</td>
<td>186,075</td>
</tr>
<tr>
<td>Government</td>
<td>85,708</td>
<td>88,975</td>
<td>93,850</td>
<td>108,917</td>
<td>110,575</td>
<td>114,942</td>
</tr>
</tbody>
</table>

*FIRE—Finance, Insurance, and Real Estate


From the expenditure side, the largest component of GSP is consistently personal consumption expenditures with a share of about 60 percent. Consumption increased from $5.4 billion in 1977 to $23.4 billion in 2000 (see table 3.4). The second largest component is government expenditures, including federal, state, and local government expenditures. The share of total government expenditures in GSP declined from 37.7 percent in 1977 to 31.7 percent in 2000. Federal expenditures, consisting of military and civilian agency spending, declined in importance in total government expenditures and made up 13.8 percent in GSP in 2000. The third largest component, private investment, was 13.6 percent of GSP in 1977, peaked at 19.1 percent in 1991 at the end of the Japanese investment boom, and gradually declined to 13.5 percent in 2000. Finally, while exports grew from a 43% share to a 53% share from 1977 to 2000, the share of imports in GSP remained stable at
Table 3.4: Expenditures as Shares of Gross State Product

<table>
<thead>
<tr>
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<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Gross State Product ($ mil)</td>
<td>8597.4</td>
<td>13078.3</td>
<td>19849.8</td>
<td>30729.8</td>
<td>34893.6</td>
<td>39394.3</td>
</tr>
<tr>
<td>Personal Consumption</td>
<td>63.1</td>
<td>66.5</td>
<td>59.5</td>
<td>58.4</td>
<td>59.7</td>
<td>59.5</td>
</tr>
<tr>
<td>Investment</td>
<td>13.6</td>
<td>13.8</td>
<td>16.2</td>
<td>19.1</td>
<td>12.5</td>
<td>13.5</td>
</tr>
<tr>
<td>Government Expenditures</td>
<td>37.7</td>
<td>32.7</td>
<td>33.3</td>
<td>30.1</td>
<td>31.3</td>
<td>31.7</td>
</tr>
<tr>
<td>State and Local</td>
<td>18.2</td>
<td>16.0</td>
<td>15.2</td>
<td>16.1</td>
<td>17.9</td>
<td>17.9</td>
</tr>
<tr>
<td>Federal</td>
<td>19.5</td>
<td>16.7</td>
<td>18.1</td>
<td>14.0</td>
<td>13.4</td>
<td>13.8</td>
</tr>
<tr>
<td>Net Exports</td>
<td>(15.9)</td>
<td>(18.2)</td>
<td>(6.2)</td>
<td>(6.7)</td>
<td>(8.3)</td>
<td>(5.2)</td>
</tr>
<tr>
<td>Exports</td>
<td>43.3</td>
<td>47.2</td>
<td>49.1</td>
<td>49.3</td>
<td>49.9</td>
<td>52.8</td>
</tr>
<tr>
<td>Imports</td>
<td>(59.2)</td>
<td>(65.4)</td>
<td>(55.3)</td>
<td>(56.0)</td>
<td>(58.2)</td>
<td>(58.0)</td>
</tr>
</tbody>
</table>


about 58%. The two major components of exports are visitor services and federal defense expenditures.

### 3.4.2 Existing Macro-econometric Models for Hawaii

The growth and changing structure of the Hawaii Economy have attracted wide interest. Economists from various groups have set up models to explain and forecast the Hawaii economy. These include university professors, economists in government planning departments, and professionals in the business community. This section summarizes existing econometric models for Hawaii. In particular, I focus on models that cover the whole economy, rather than a particular sector.

The first comprehensive model for Hawaii was constructed in the mid 1970s by Ghali and Renaud (1975). The Ghali and Renaud model (hereafter the GR model) is a traditional Keynesian macroeconometric model of aggregate demand components such as private consumption, private investment, government expenditure, and external trade. Industrial employment adjusts to meet total final demand and the unemployment rate is calculated as an identity. The private sector aggregate wage rate varies with civilian unemployment following a non-linear Phillips-curve and the wage rate in the public sector is assumed
to be a linear function of the wage rate in the private sector. The two wage rates and employment in the two sectors determine total wage income, which in turn drives the labor force at various age groups. Interest rates and prices are exogenously determined, justified by Ghali and Renaud (1975) on the ground that "the determinants of prices, money and interest belong more appropriately in models of the national economy". The GR model is estimated one equation at a time using Ordinary Least Squares (OLS) static regressions. Ghali and Renaud acknowledge the possibility of simultaneity bias and suggest correcting for this bias using modified Two Stage Least Squares (TSLS).

In addition to the GR model, the State of Hawaii Department of Business, Economic Development and Tourism (DBEDT) maintains a Hawaii projection and simulation model (hereafter the DBEDT model). The purpose of the model is to provide long-term projections for Hawaii's demographic characteristics and key economic indicators, both for the entire state and individual counties, to guide DBEDT and other state agencies in policy formulation. The model combines the traditional Keynesian macro econometric model with an input-output submodel to determine a pattern of industry production that satisfies existing final demand. Like other regional models, an economic migration submodel adjusts local population in response to excess demand in the labor market. A cohort algorithm governs the growth and age progression of local population. A major deficiency of the DBEDT model is the lack of supply treatment. In the model, shocks to final demand elicit a multiplier response in industrial output after a lag. Resulting excess demand for labor is completely satisfied by inward migration with no upward pressure on wages or prices. The long-run growth path of the economy is determined by exogenous growth in final demand and real productivity, along with evolution of the population's age structure via the cohort model. For other critiques of the model, see Bonham and Gangnes (1995).

In the business community, a top-down regional economic forecasting model was constructed by Tucson Economic Consulting (TEC) in 1993 for the marketing

\footnote{Ghali and Renaud (1975) p. 11.}
and planning purposes of Hawaiian Electric Company and its sister companies, Hawaii Electric Light Company and Maui Electric Company (UHERO, 2000). The Hawaiian Electric Company model had been maintained by TEC until the University of Hawaii Economic Research Organization (UHERO) took over in 1998 (hereafter the UHERO model). Unlike the previous two annual models that rely on income and product accounts, the UHERO model is a quarterly model of economic and demographic data such as: 1) employment and average hourly earnings by major industries; 2) local area personal income by major categories and detailed earnings by industry; 3) local labor supply (population) and the main components of population change—births, deaths, and net migration (in the case of Oahu, military troops and their dependents are also considered); and 4) other economic indicators of local construction, tourism, and prices. The UHERO model consists of two blocks of equations: one for Oahu and the other for the neighbor islands (Maui, Hawaii, and Kauai). The design of the Oahu and neighbor islands models relies on the “export base” concept where the primary export industries are tourism and military defense services. Industries like transportation and retail trade serve both export and local markets. Employment in export and local industries in turn produces the bulk of local personal income. Other sources of income are determined by national influences, including transfer payments, social security contributions, and dividend and interest payments. Total personal income then acts as the final demand determinant for goods and services. Besides the impacts of export industries, Oahu and the neighbor island economies are further linked to the national and international economies by interest rates, inflation and tax rates. Demographic analysis is integrated into the model such that economic activity in employment and personal income interacts directly with population change. Thus, population is both a cause and an effect of local economic growth. The behavioral equations in the UHERO model are estimated using single-equation cointegration analysis and specified in error correction form.

The three Hawaii models summarized above characterize the two typical approaches to regional econometric modelling. The first approach, represented by the GR model and the DBEDT model, follows traditional income and product
accounts macro theory. They require expenditure-side income and product accounts data at the regional level. Such data are not typically available from national data sources and must be constructed by local agencies. Therefore, these models cannot be used to generate high-frequency forecasts on a timely basis. The second approach, represented by the UHERO model, uses high frequency economic data that is readily available and frequently reported. However, the general structure lacks theory guidance. A typical model utilizes the “export base” concept and categorizes industries into “export industry” and “local industry”. Export sectors generate initial income which feeds into local sectors and produce induced demand and income. In the literature, there has not been any effort to combine the theoretical structure and available data in an informative way.

3.5 A Pseudo Income and Product Account Model for Hawaii

In this paper, I propose a model that uses BVAR blocks to mimic the components of traditional income and product accounts and follows Keynesian aggregate demand theory in forming the blocks. As such, the model can be labelled a “pseudo income and product account model”. It offers an alternative to regional econometric modeling. This section describes the model specification and lists the estimation results.

3.5.1 Model Structure and Prior-selection Mechanism

From section 3.4.1, a comprehensive model for the State of Hawaii needs to capture four components of GSP: personal consumption, investment, government expenditures, and import and export. In the pseudo income and product account BVAR forecasting model, different blocks are constructed to mimic these components. The BEA reports only income-side GSP data. There have been various efforts to construct expenditure side GSP data for the State of Hawaii, see Oshima (1965), Shang, Albrecht, and Ifuku (1970) and DBEDT (1989).
Figure 3.1: The Interactions of Hawaii BVAR System
expenditure categories (see figure 3.1). In the figure, each rectangle represents a BVAR model block and each hexagon stands for one external driving force. The U.S. and Japan are the two major driving forces for the Hawaii economy, not only because of Hawaii's special geographical location, but also because of the close economic ties formed historically.

The Hawaii tourism block characterizes the export component of the expenditure account. It captures demand from the rest of the country and world for the tourism commodities and services produced in the islands. In the Hawaii core block, collective local economic indicators are determined by overall tourism activity and other U.S. and Japan drivers. This is justified on the grounds that the export base includes not only tourism, but also sectors such as federal defense, wholesale and retail trade, and agriculture. In this sense, the core block can be viewed as an extension of the import and export component in the GSP accounts. The Hawaii investment block is intended to capture investment activity in Hawaii, especially residential and non-residential fixed investment. Finally, the Hawaii consumption block includes both private and public consumption. General excise and use tax base data is used to proxy for local consumption, because no high frequency consumption data exists at the regional level.13

There are six hyper-parameters to be determined in each BVAR block: the overall tightness ($\lambda_1$), the relative tightness of other variables to the dependent variable ($\lambda_2$), the lag decay parameter ($\lambda_3$), the tightness on constant ($\lambda_4$), the weight on the sums of coefficients prior ($\lambda_5$), and the weight on the dummy initial observation prior ($\lambda_6$). These hyper-parameters are chosen to minimize the General Forecast Error Second Moment Matrix (GFESM) (Clements and Hendry, 1998). In particular, I minimize the log determinant of the variance-covariance matrix of the one- to eight-quarters ahead forecast errors. Compared to the widely adopted MSFE and Theil’s U statistic criteria, GFESM has the advantage of being invariant to non-singular, scale-preserving linear transformations (Clements and Hendry, 1998).

In this respect, Hawaii benefits from its rich data set. Hawaii is one of the few states in the union that levies an excise and use tax on all activities. The rates applied are different for wholesale and retail transactions, see below.
1998).

To select prior, each BVAR block is estimated using data from 1980Q1 through 1997Q4. One- to eight-quarters ahead forecast errors for all \( n \) variables of interest are generated and stacked to form an \( 8n \times 8n \) error vector \( (e_t) \). The error variance-covariance matrix and its log determinant are calculated as \( \Phi = E[e_t'e_t] \) and \( \log |\Phi| \), call this \( \log |\Phi|_1 \). Next, the estimation ending period is moved one quarter ahead to 1998Q1 and the model is re-estimated. Another set of one- to eight-quarters ahead forecast errors is obtained and thus a new log determinant \( \log |\Phi|_2 \). This process is repeated \( N \) times until we reach the end of the sample period. We then calculate the simple mean \( (\log |\Phi|_{\text{mean}}) \) of all the log determinants, \( \log |\Phi|_1, \log |\Phi|_2, \ldots, \log |\Phi|_N \). Our objective is to search over a range of prior values and find the minimum \( \log |\Phi|_{\text{mean}} \). In the next section, I list the data series used in each BVAR block and priors selected.

### 3.5.2 Block Details and Selected Priors

This section lists the prior selection and estimation result for the four blocks in the Hawaii BVAR forecasting system. Projections for external U.S. and Japan drivers are taken from the most recent 20 year long-term forecasts generated by UHERO. An alternative is to construct a separate BVAR block for the two driver economies. In the literature, a number of BVAR forecasting models have been constructed for the U.S., including Sims (1993), Zha (1998), Chin (1999), and Robertson and Tallman (1999). Although no BVAR model exists for Japan, VAR models have been established to isolate causal factors for the economic slump experienced in the 1990s (Bayoumi, 2001; Ramaswamy and Rendu, 2000). Considering that a related goal of the paper is to compare forecasts from the BVAR forecasting system to those from the UHERO model, it is preferable to use the same forecasts for external drivers.

---

\(^{14}\)The number of variables of interest varies for different blocks. For instance, we are interested in four variables in the Hawaii tourism block: total visitor arrivals, the hotel room rate, hotel occupancy rate, and hotel rental tax base.
Tourism has dominated the Hawaii economy since the early 1980s. The share of visitor expenditures was 41.5% in total exports in 1980, whereas defense spending was 22.7% and sugar and pineapple were 6.7% and 2.6% respectively. By 1990, the share of defense expenditures had dropped to only 18.6% and that of sugar and pineapple to 1.7% and 1% respectively. The share of visitor expenditures, on the other hand, had mushroomed to 58.6% of total exports.\textsuperscript{15}

Tourism is heavily influenced by the two driver economies. Visitors from the U.S. and Japan consistently account for more than 85 percent of total arrivals to the islands during the last three decade (see figure 3.2). As such, the economic health of the two economies is crucial to the sustained growth of the islands. In the Hawaii tourism block, I use the following variables as drivers: real Gross Domestic Product (GDP) for the U.S. and Japan, Consumer Price Indices (CPI) for the U.S.

\textsuperscript{15}Numbers come from \textit{Hawaii’s Economy}, 3rd quarter 1995.
and Japan, and the yen/dollar exchange rate. The variables of interest include the total visitor count to Hawaii, the average daily hotel room rate, average daily hotel occupancy rate, and the hotel rental general excise tax base. For further details on variable choice, refer to Zhou (2003a). Table 3.5 lists the original series and data sources. Monthly series are aggregated to quarterly and seasonally adjusted.

Table 3.5: Variables in the Hawaii Tourism Block

<table>
<thead>
<tr>
<th>Mnemonic</th>
<th>Description</th>
<th>Units</th>
<th>Freq.</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>gdpr_us</td>
<td>U.S. real gross domestic product</td>
<td>Bil. 96$</td>
<td>Q</td>
<td>BEA</td>
</tr>
<tr>
<td>gdpr jp</td>
<td>Japan real gross domestic product</td>
<td>Bil. 95Yen</td>
<td>Q</td>
<td>ESRI</td>
</tr>
<tr>
<td>cpins_us</td>
<td>U.S. consumer price index</td>
<td>82-84=100</td>
<td>M</td>
<td>BLS</td>
</tr>
<tr>
<td>cpi.jp</td>
<td>Japan consumer price index</td>
<td>95=100</td>
<td>M</td>
<td>SBSC</td>
</tr>
<tr>
<td>yxrns jp</td>
<td>Yen/dollar exchange rate</td>
<td>yen/$</td>
<td>M</td>
<td>FED</td>
</tr>
<tr>
<td>visns_hi</td>
<td>Hawaii total visitor arrivals</td>
<td>000s</td>
<td>M</td>
<td>DBEDT</td>
</tr>
<tr>
<td>prmns_hi</td>
<td>Hawaii avg. hotel room rate</td>
<td>$</td>
<td>M</td>
<td>DBEDT</td>
</tr>
<tr>
<td>ocup%ns_hi</td>
<td>Hawaii avg. hotel occupancy rate</td>
<td>%</td>
<td>M</td>
<td>DBEDT</td>
</tr>
<tr>
<td>txhotbsns_hi</td>
<td>Hawaii hotel general excise tax base</td>
<td>000$</td>
<td>M</td>
<td>DTAX</td>
</tr>
</tbody>
</table>

BEA: Bureau of Economic Analysis, U.S.
FED: St. Louis Federal Reserve Bank, U.S.
ESRI: Economic and Social Research Institute, Japan.
SBSC: Statistics Bureau and Statistics Center, Japan.
DTAX: Department of Taxation, State of Hawaii.

To select priors, I search over a range for each $\lambda_i, i = 1, 2, \ldots, 6$. The prior is selected to minimize the log determinant of the forecast error variance-covariance matrix as described earlier. I search over the following ranges: the overall tightness parameter $\lambda_1$ from 0.1 to 0.5 with an increment of 0.1; the relative tightness parameter $\lambda_2$ from 0.1 to 0.5 with an increment of 0.1; the lag decay parameter $\lambda_3$ from 0.2 to 1 with an increment of 0.2; the tightness on constant $\lambda_4$ from 0.1 to 0.5 with an increment of 0.1; the weight on the sums of coefficients prior $\lambda_5$ from 3 to 7 with an increment of 1, and the weight on the dummy initial observation prior $\lambda_6$ from 3 to 7 with an increment of 1. Altogether there are 15,625 different combinations of prior specifications. The priors chosen are listed in table 3.6.
Table 3.6: Priors Selected for the Hawaii Tourism Block

<table>
<thead>
<tr>
<th>Prior</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\lambda_1$</td>
<td>Overall tightness</td>
<td>0.5</td>
</tr>
<tr>
<td>$\lambda_2$</td>
<td>Relative tightness</td>
<td>0.5</td>
</tr>
<tr>
<td>$\lambda_3$</td>
<td>Leg decay</td>
<td>0.8</td>
</tr>
<tr>
<td>$\lambda_4$</td>
<td>Tightness on constant</td>
<td>0.5</td>
</tr>
<tr>
<td>$\lambda_5$</td>
<td>Sums of coefficient</td>
<td>7</td>
</tr>
<tr>
<td>$\lambda_6$</td>
<td>Dummy initial observation</td>
<td>3</td>
</tr>
</tbody>
</table>

This implies that we have relatively weak priors on the constant and the random walk approximation for the dependent variable. Coefficients on other variables have prior variances half the size of those on the dependent variable. Decay on higher order lags is slightly less than harmonic. Last, the cointegration priors chosen lean more towards a model in first differenced format.

**Hawaii Core Block**

Besides tourism, Hawaii exports other goods and services such as agricultural products and federal defense. Payments in these export industries in turn generate derived demand for local industries like manufacturing, transportation, communications and utilities, and business services. Considering size limitations, I combine sectors together and study aggregate measurements like personal income, total jobs, and unemployment. On the nominal side, Hawaii is influenced by the U.S. through price correlations. Being a state in the union, the aggregate price level in Hawaii naturally follows the trend of the U.S. prices (see figure 3.3). The correlation between the Honolulu CPI and U.S. CPI is as high as 99% over the entire sample period. In the Hawaii core block, the driver series include total visitor arrivals to Hawaii, the U.S. real GDP, Japan real GDP, the U.S. CPI, and the U.S. national defense expenditures. Table 3.7 lists the original series and data sources. Monthly series are aggregated to quarterly and seasonally adjusted.

Different prior combinations are tried and the prior is chosen to minimize the log determinant of the variance-covariance matrix of one- to eight-quarters ahead forecast errors. I search over the following ranges: the overall tightness parameter
Figure 3.3: U.S. CPI and Honolulu CPI 1980Q1-2002Q4
Table 3.7: Variables in the Hawaii Core Block

<table>
<thead>
<tr>
<th>Mnemonic</th>
<th>Description</th>
<th>Units</th>
<th>Freq.</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>gdpr_us</td>
<td>U.S. real gross domestic product</td>
<td>Bil. 96$</td>
<td>Q</td>
<td>BEA</td>
</tr>
<tr>
<td>gdpr_jp</td>
<td>Japan real gross domestic product</td>
<td>Bil. 95Yen</td>
<td>Q</td>
<td>ESRI</td>
</tr>
<tr>
<td>cpins_us</td>
<td>U.S. consumer price index</td>
<td>82-84=100</td>
<td>M</td>
<td>BLS</td>
</tr>
<tr>
<td>def_us</td>
<td>U.S. national defense expenditures</td>
<td>Bil.$</td>
<td>Q</td>
<td>BEA</td>
</tr>
<tr>
<td>visns_hi</td>
<td>Hawaii total visitor arrivals</td>
<td>000s</td>
<td>M</td>
<td>DBEDT</td>
</tr>
<tr>
<td>yp_hi</td>
<td>Hawaii personal income</td>
<td>Mil.$</td>
<td>Q</td>
<td>BEA</td>
</tr>
<tr>
<td>eeans_hi</td>
<td>Hawaii total non-agricultural jobs</td>
<td>000s</td>
<td>M</td>
<td>BLS</td>
</tr>
<tr>
<td>urns_hi</td>
<td>Hawaii civilian unemployment rate</td>
<td>%</td>
<td>M</td>
<td>BLS</td>
</tr>
<tr>
<td>cpi_hon</td>
<td>Honolulu consumer price index</td>
<td>82-84=100</td>
<td>S</td>
<td>BLS</td>
</tr>
</tbody>
</table>

BEA: Bureau of Economic Analysis, U.S.
ESRI: Economic and Social Research Institute, Japan.
S: Semi-annual, series is interpolated to quarterly for the model.

\[ \lambda_1 \text{ from } 0.1 \text{ to } 0.5 \text{ with an increment of } 0.1; \] the relative tightness parameter \( \lambda_2 \)
\[ \text{from } 0.1 \text{ to } 0.5 \text{ with an increment of } 0.1; \] the lag decay parameter \( \lambda_3 \)
\[ \text{from } 0.2 \text{ to } 1 \text{ with an increment of } 0.2; \] the tightness on constant \( \lambda_4 \)
\[ \text{from } 0.1 \text{ to } 0.5 \text{ with an increment of } 0.1; \] the weight on the sums of coefficients prior \( \lambda_5 \)
\[ \text{from } 3 \text{ to } 7 \text{ with an increment of } 1, \] and the weight on the dummy initial observation prior \( \lambda_6 \)
\[ \text{from } 3 \text{ to } 7 \text{ with an increment of } 1. \] Altogether there are 15,625 different combinations of prior specifications. The parameters selected are listed in table 3.8.

Table 3.8: Priors Selected for the Hawaii Core Block

<table>
<thead>
<tr>
<th>Prior</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>\bar{\lambda}_1</td>
<td>Overall tightness</td>
<td>0.3</td>
</tr>
<tr>
<td>\lambda_2</td>
<td>Relative tightness</td>
<td>0.5</td>
</tr>
<tr>
<td>\lambda_3</td>
<td>Leg decay</td>
<td>0.8</td>
</tr>
<tr>
<td>\lambda_4</td>
<td>Tightness on constant</td>
<td>0.5</td>
</tr>
<tr>
<td>\lambda_5</td>
<td>Sums of coefficient</td>
<td>3</td>
</tr>
<tr>
<td>\lambda_6</td>
<td>Dummy initial observation</td>
<td>7</td>
</tr>
</tbody>
</table>

This means that we have relatively weak priors on the constant but a relatively
strong prior on the random walk approximation for the right-hand-side variable. Coefficients on other variables have prior variances half the size of those on the dependent variable. Decay on higher order lags is less than harmonic. Finally, the cointegration priors favor a form where series are integrated and cointegrate among themselves.

**Hawaii Investment Block**

The Hawaii Investment block is borrowed from Zhou (2003b). Variables of interest include Hawaii construction sector jobs, Hawaii single-family and condominium resales, and the contracting tax base. Private building permits and government contracts awarded are included as leading indicators (Dua, Miller, and Smith, 1999). The driving forces include total visitor arrivals, the U.S. mortgage rate, Hawaii personal income, and the Hawaii civilian unemployment rate. For details of the model, see Zhou (2003b). Table 3.9 lists the original series and data sources. Monthly series are aggregated to quarterly and seasonally adjusted.

Table 3.9: Variables in the Hawaii Investment Block

<table>
<thead>
<tr>
<th>Mnemonic</th>
<th>Description</th>
<th>Units</th>
<th>Freq.</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>ecns_hi</td>
<td>Hawaii construction jobs</td>
<td>000s</td>
<td>M</td>
<td>BLS</td>
</tr>
<tr>
<td>khns_hi</td>
<td>Hawaii single-family and condominium resales</td>
<td>Units</td>
<td>Q</td>
<td>PRUD</td>
</tr>
<tr>
<td>txconns_hi</td>
<td>Hawaii contracting GET base</td>
<td>000$</td>
<td>M</td>
<td>DTAX</td>
</tr>
<tr>
<td>kpns_hi</td>
<td>Hawaii private and public building permits</td>
<td>Mil.$</td>
<td>Q</td>
<td>DBEDT</td>
</tr>
<tr>
<td>rmort_us</td>
<td>U.S. 30 year conventional mortgage rate</td>
<td>%</td>
<td>M</td>
<td>FED</td>
</tr>
<tr>
<td>yp_hi</td>
<td>Hawaii personal income</td>
<td>Mil.$</td>
<td>Q</td>
<td>BEA</td>
</tr>
<tr>
<td>urns_hi</td>
<td>Hawaii civilian unemployment rate</td>
<td>%</td>
<td>M</td>
<td>BLS</td>
</tr>
<tr>
<td>visns_hi</td>
<td>Hawaii total visitor arrivals</td>
<td>000s</td>
<td>M</td>
<td>DBEDT</td>
</tr>
</tbody>
</table>

PRUD: Prudential Locations research department, State of Hawaii.
DTAX: Department of Taxation, State of Hawaii.
FED: Federal Reserve Bank at St. Louis, U.S.
BEA: Bureau of Economic Analysis, U.S.

Priors are selected to minimize the log determinant of the variance-covariance matrix of the one- to eight-quarters ahead forecast errors. For details on search
range, see Zhou (2003b). The priors selected are listed in table 3.10. This implies that we have strong priors on constant and the random walk approximation for the dependent variable. Coefficient prior variances of other variables are treated the same as those on the dependent variable. Higher order lags follow a decay pattern faster than harmonic decay. Finally, both cointegration priors are very weak.

Table 3.10: Priors Selected for the Hawaii Investment Block

<table>
<thead>
<tr>
<th>Prior</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\lambda_1$</td>
<td>Overall tightness</td>
<td>0.2</td>
</tr>
<tr>
<td>$\lambda_2$</td>
<td>Relative tightness</td>
<td>1</td>
</tr>
<tr>
<td>$\lambda_3$</td>
<td>Leg decay</td>
<td>1.4</td>
</tr>
<tr>
<td>$\lambda_4$</td>
<td>Tightness on constant</td>
<td>0.02</td>
</tr>
<tr>
<td>$\lambda_5$</td>
<td>Sums of coefficient</td>
<td>0.08</td>
</tr>
<tr>
<td>$\lambda_6$</td>
<td>Dummy initial observation</td>
<td>0.02</td>
</tr>
</tbody>
</table>

**Hawaii Consumption Block**

The Hawaii consumption block is in essence a tax base block. With no high frequency consumption data available, proxy variables are used. The state of Hawaii benefits from its rich data set in this respect. Unlike other states, Hawaii levies a general excise and use tax (GET) on all transactions. The rate applicable is different depending on the type of transactions involved. In particular, a 4% ad valorem tax applies to all retail transactions and a 0.5% privilege tax applies to manufacturers and wholesalers. Insurance solicitors and agents are taxed at a 0.15% rate on their commissions rather than their gross sales. The different rate is not levied by general classification of firms, but by the type of transaction. For instance, a manufacturer who sells both to wholesalers and at retail pays the different rate on each.\(^{16}\) For more information on the Hawaii GET, see Fox (1989).

The State of Hawaii Department of Taxation reports both the base and receipts on the GET at the state and county levels on a monthly basis. The tax base and

\(^{16}\)There might exist a double-counting problem. For instance, a construction material dealer wholesales to a developer and pays 0.5% privilege tax. Later when a consumer hires the developer and remodels her house, she pays a 4% retail tax on both service and materials used.
Table 3.11: Variables in the Hawaii Consumption Block

<table>
<thead>
<tr>
<th>Mnemonic</th>
<th>Description</th>
<th>Units</th>
<th>Freq.</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>yp_hi</td>
<td>Hawaii personal income</td>
<td>Mil.$</td>
<td>Q</td>
<td>BEA</td>
</tr>
<tr>
<td>eeans_hi</td>
<td>Hawaii total non-agricultural jobs</td>
<td>000s</td>
<td>M</td>
<td>BLS</td>
</tr>
<tr>
<td>urns_hi</td>
<td>Hawaii civilian unemployment rate</td>
<td>%</td>
<td>M</td>
<td>BLS</td>
</tr>
<tr>
<td>cpi_hon</td>
<td>Honolulu consumer price index</td>
<td>82-84=100</td>
<td>S</td>
<td>BLS</td>
</tr>
<tr>
<td>visns_hi</td>
<td>Hawaii total visitor arrivals</td>
<td>000s</td>
<td>M</td>
<td>DBEDT</td>
</tr>
<tr>
<td>txexcbsns_hi</td>
<td>Hawaii 4% excise tax base*</td>
<td>000$</td>
<td>M</td>
<td>CALC</td>
</tr>
<tr>
<td>txusebsns_hi</td>
<td>Hawaii 0.5% use tax base</td>
<td>000$</td>
<td>M</td>
<td>CALC</td>
</tr>
<tr>
<td>txinrbsns_hi</td>
<td>Hawaii 0.15% insurance GET base</td>
<td>000$</td>
<td>M</td>
<td>CALC</td>
</tr>
</tbody>
</table>

BEA: Bureau of Economic Analysis, U.S.
S: Semi-annual, series is interpolated to quarterly for the model.
*: Contracting and hotel rental tax bases are excluded.

receipts are categorized into retailing, services, contracting, hotel, theater, etc. It is not feasible to model all tax base series in a single BVAR block due to size limitations. Some aggregation is needed. From an empirical consideration, if tax bases are separately forecasted, overall tax receipts can be calculated by applying individual tax rates to the respective category. Since the hotel and contracting tax bases are modelled in the tourism and the investment blocks respectively, we organize the remaining tax bases into three categories—those incurring 4%, 0.5% and 0.15% respectively. Driver variables in the block include collective economic indicators such as personal income, total non-agricultural jobs, the Honolulu CPI and the civilian unemployment rate and total visitor arrivals because part of the tax revenues come from visitor consumption (for instance, retailing, services, theater, and amusement). Table 3.11 lists the series used and data sources. Monthly series are aggregated to quarterly and seasonally adjusted.

Different prior combinations are tried and the final prior is chosen to minimize the log determinant of the variance-covariance matrix of the one- to eight-quarters ahead forecast errors. In particular, the searching range is as follows: the overall tightness parameter $\lambda_1$ from 0.1 to 0.5 with an increment of 0.1; the relative
tightness parameter $\lambda_2$ from 0.1 to 0.5 with an increment of 0.1; the lag decay parameter $\lambda_3$ from 0.2 to 1 with an increment of 0.2; the tightness on constant $\lambda_4$ from 0.1 to 0.5 with an increment of 0.1; the weight on the sums of coefficients prior $\lambda_5$ from 3 to 7 with an increment of 1, and the weight on the dummy initial observation prior $\lambda_6$ from 3 to 7 with an increment of 1. Altogether there are 15,625 different combinations of prior specifications. The priors selected are listed in table 3.12.

Table 3.12: Priors Selected for the Hawaii Consumption Block

<table>
<thead>
<tr>
<th>Prior</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\lambda_1$</td>
<td>Overall tightness</td>
<td>0.5</td>
</tr>
<tr>
<td>$\lambda_2$</td>
<td>Relative tightness</td>
<td>0.5</td>
</tr>
<tr>
<td>$\lambda_3$</td>
<td>Leg decay</td>
<td>1</td>
</tr>
<tr>
<td>$\lambda_4$</td>
<td>Tightness on constant</td>
<td>0.5</td>
</tr>
<tr>
<td>$\lambda_5$</td>
<td>Sums of coefficient</td>
<td>7</td>
</tr>
<tr>
<td>$\lambda_6$</td>
<td>Dummy initial observation</td>
<td>7</td>
</tr>
</tbody>
</table>

This implies that we have relatively weak priors on the constant and the random walk approximation for the dependent variable. Coefficients on other variables have prior variances half the size of those on the dependent variable. Decay on higher order lags follows the harmonic pattern. The cointegration priors chosen favor a form of integrated series and cointegration.

### 3.6 Model Simulations

The purpose of model simulations is to evaluate the performance of the newly estimated BVAR forecasting system in response to specific changes in the exogenous variables. In this way, we can see how endogenous variables in the system respond to exogenous shocks, and gain insight into the relationships and correlations selected by the block structure of the BVAR selection method. For the simulation reported below, the exogenous inputs into the model (U.S. and Japan drivers) are borrowed from the most recent UHERO forecasts. These include U.S.
and Japan real GDP \((gdpr\_us\) and \(gdpr\_jp))\), U.S. and Japan consumer price indices \((cpi\_us\) and \(cpi\_jp))\), and the yen/dollar exchange rate \((yxr\_jp))\). Two additional drivers (U.S. 30-year conventional mortgage rate, \(rmort\_us\), and U.S. national defense expenditures, \(def\_us\)) are not forecasted in the UHERO system. For simplicity, I assume zero change for both series throughout the forecast horizon, i.e., forecasts at all horizons are equal to the last sample observation (2003Q1).\(^{17}\)

In this simulation exercise, I am interested in the impacts of exogenous shocks to U.S. and Japan real GDP on the following Hawaii variables: total visitor arrivals \((vis\_hi))\), the hotel room rate \((prm\_hi))\), personal income \((yp\_hi))\), total non-agriculture jobs \((eea\_hi))\), and the total GET tax base \((txbs\_hi))\). Specifically, the exogenous shocks studied are: 1) a 1% increase in baseline U.S. real GDP, sustained throughout the six years of simulation period; 2) a 1% increase in baseline Japan real GDP, sustained throughout the six years of simulation period.

1% Increase in U.S. GDP

The impact of a 1% increase in U.S. real GDP is summarized in table 3.13. A 1% increase in U.S. real GDP sustained throughout the simulation period raises total visitor arrivals by 0.43% in the first year, gradually declining to 0.38% after six years. The increase in visitors drives up hotel room rates. The increase in room rate peaks in the second year, rising by as much as 0.78% before tapering off to 0.66% in 2008. Increases in visitors also bring extra income to the state, but it takes longer for the effect to set in. Nominal income rises by only 0.09% the first year after the shock, gradually increasing to 0.23% after six years. The GET tax base follows a similar pattern but with a larger percentage increase each year of the simulation. GET tax base increases by 0.11% in 2003 with the rate converging to 0.29% in 2008. Compared with personal income and the GET tax base, non-agriculture jobs respond much less. The increase in non-agriculture jobs is only 0.01% the first year after the shock and approaches 0.09% in 2008. Figure

\(^{17}\)This might not be a good assumption considering the recent fiscal and monetary policy changes. However, exogenous shocks studied here involve only real GDP and yen/dollar exchange rate. Additional efforts are surely justified to generate more reasonable forecasts and to simulate shocks to the two variables.
Table 3.13: Impacts of 1% Increase in U.S. Real GDP

<table>
<thead>
<tr>
<th></th>
<th>2003</th>
<th>2004</th>
<th>2005</th>
<th>2006</th>
<th>2007</th>
<th>2008</th>
</tr>
</thead>
<tbody>
<tr>
<td>U.S. Real GDP Increase</td>
<td>95.33</td>
<td>95.33</td>
<td>95.33</td>
<td>95.33</td>
<td>95.33</td>
<td>95.33</td>
</tr>
<tr>
<td>Visitor Arrivals</td>
<td>6449.11</td>
<td>6522.98</td>
<td>6646.99</td>
<td>6825.96</td>
<td>6989.46</td>
<td>7122.63</td>
</tr>
<tr>
<td>Percent Difference</td>
<td>0.431</td>
<td>0.423</td>
<td>0.418</td>
<td>0.400</td>
<td>0.387</td>
<td>0.374</td>
</tr>
<tr>
<td>Hotel Room Rate</td>
<td>148.32</td>
<td>155.63</td>
<td>163.04</td>
<td>171.05</td>
<td>179.54</td>
<td>187.96</td>
</tr>
<tr>
<td>Percent Difference</td>
<td>0.338</td>
<td>0.780</td>
<td>0.726</td>
<td>0.703</td>
<td>0.682</td>
<td>0.662</td>
</tr>
<tr>
<td>Personal Income</td>
<td>37.844</td>
<td>38.493</td>
<td>39.149</td>
<td>39.833</td>
<td>40.528</td>
<td>41.190</td>
</tr>
<tr>
<td>Percent Difference</td>
<td>0.086</td>
<td>0.206</td>
<td>0.222</td>
<td>0.228</td>
<td>0.230</td>
<td>0.232</td>
</tr>
<tr>
<td>Non-ag. Jobs</td>
<td>557.335</td>
<td>561.212</td>
<td>564.514</td>
<td>567.900</td>
<td>571.248</td>
<td>574.256</td>
</tr>
<tr>
<td>Percent Difference</td>
<td>0.012</td>
<td>0.067</td>
<td>0.084</td>
<td>0.088</td>
<td>0.091</td>
<td>0.092</td>
</tr>
<tr>
<td>GET Tax Base</td>
<td>54.056</td>
<td>54.622</td>
<td>55.791</td>
<td>57.045</td>
<td>58.342</td>
<td>59.569</td>
</tr>
<tr>
<td>Percent Difference</td>
<td>0.114</td>
<td>0.273</td>
<td>0.291</td>
<td>0.295</td>
<td>0.295</td>
<td>0.294</td>
</tr>
</tbody>
</table>

Note: Figures in row one are absolute shocks. The remaining figures show levels after the shock and percent differences from the baseline simulation. U.S. real GDP increase is in billions of 1996 dollars. Visitor arrivals are in thousands of persons. The hotel room rate is in dollars. Nominal personal Income is in billions of dollars. Non-agriculture jobs are in thousands of persons. The GET tax base is in billions of dollars.

3.4 plots the impact of a 1% increase in U.S. GDP on the five Hawaii variables.

1% Increase in Japan Real GDP

The impact of a 1% increase in Japan real GDP is summarized in table 3.14. The impact on total visitor arrivals has a time lag and does not peak until the second year. This is in contrast with the impact of a 1% increase in U.S. GDP that peaks immediately after the shock. The 1% increase in Japan real GDP results in a larger visitor arrivals increase cumulatively, maybe because it does not cause the hotel rate to rise as much, thus having a smaller dampening effect. The increase in the hotel room rate following a 1% increase in Japan real GDP is 0.05–0.10% smaller than that brought about by a 1% increase in U.S. real GDP.
Figure 3.4: Impact of 1% Increase in U.S. Real GDP (% Chg. from Baseline)
Higher visitor arrivals results in higher income growth in Hawaii. Nominal personal income rises by 0.15% in 2003 following the Japan GDP shock, compared with a 0.09% increase following the U.S. GDP shock. In 2006, the gap widens to as much as 0.10%. Interestingly, higher visitor arrivals does not bring in extra tax dollars or job growth to the state. Increases in GET tax base and non-agriculture jobs are about the same as those following the U.S. GDP shock. Figure 3.5 plots the impacts of a 1% increase in U.S. GDP on the five Hawaii variables.

Table 3.14: Impacts of 1% Increase in Japan Real GDP

<table>
<thead>
<tr>
<th></th>
<th>2003</th>
<th>2004</th>
<th>2005</th>
<th>2006</th>
<th>2007</th>
<th>2008</th>
</tr>
</thead>
<tbody>
<tr>
<td>Japan Real GDP increase</td>
<td>5377.58</td>
<td>5377.58</td>
<td>5377.58</td>
<td>5377.58</td>
<td>5377.58</td>
<td>5377.58</td>
</tr>
<tr>
<td>Visitor Arrivals</td>
<td>6445.81</td>
<td>6533.38</td>
<td>6655.77</td>
<td>6835.33</td>
<td>6999.10</td>
<td>7132.58</td>
</tr>
<tr>
<td>Percent Difference</td>
<td>0.380</td>
<td>0.583</td>
<td>0.551</td>
<td>0.537</td>
<td>0.526</td>
<td>0.515</td>
</tr>
<tr>
<td>Hotel Room Rate</td>
<td>148.39</td>
<td>155.48</td>
<td>162.93</td>
<td>170.96</td>
<td>179.46</td>
<td>187.88</td>
</tr>
<tr>
<td>Percent Difference</td>
<td>0.386</td>
<td>0.682</td>
<td>0.661</td>
<td>0.649</td>
<td>0.634</td>
<td>0.621</td>
</tr>
<tr>
<td>Personal Income</td>
<td>37.868</td>
<td>38.531</td>
<td>39.190</td>
<td>39.874</td>
<td>40.568</td>
<td>41.229</td>
</tr>
<tr>
<td>Percent Difference</td>
<td>0.148</td>
<td>0.304</td>
<td>0.329</td>
<td>0.332</td>
<td>0.330</td>
<td>0.326</td>
</tr>
<tr>
<td>Non-ag. Jobs</td>
<td>557.331</td>
<td>561.190</td>
<td>564.487</td>
<td>567.868</td>
<td>571.205</td>
<td>574.201</td>
</tr>
<tr>
<td>Percent Difference</td>
<td>0.011</td>
<td>0.063</td>
<td>0.079</td>
<td>0.083</td>
<td>0.083</td>
<td>0.083</td>
</tr>
<tr>
<td>GET Tax Base</td>
<td>54.042</td>
<td>54.612</td>
<td>55.791</td>
<td>57.045</td>
<td>58.341</td>
<td>59.566</td>
</tr>
<tr>
<td>Percent Difference</td>
<td>0.088</td>
<td>0.256</td>
<td>0.291</td>
<td>0.295</td>
<td>0.294</td>
<td>0.290</td>
</tr>
</tbody>
</table>

Note: Figures in row one are absolute shocks. The remaining figures show levels after the shock and percent differences from the baseline simulation. U.S. real GDP increase is in billions of 1996 dollars. Visitor arrivals are in thousands of persons. The hotel room rate is in dollars. Nominal personal Income is in billions of dollars. Non-agriculture jobs are in thousands of persons. The GET tax base is in billions of dollars.
Figure 3.5: Impact of 1% Increase in Japan Real GDP (% Chg. from Baseline)
3.7 Forecast Evaluation

In this section, I formally evaluate the forecasting performance of the newly established pseudo income and product account BVAR forecasting model (hereafter BVAR-model). To provide some benchmarks, the evaluation is done relative to three rival models: 1) a simple random walk model in which the best forecast for next quarter and all future quarters is the observed value this quarter (hereafter RW-model); 2) the UHERO model as discussed in section 3.4 (hereafter UHERO-model); 3) the cointegrating VAR tourism model identified in Zhou (2003a) (hereafter CointTour-model). Due to space limitation and model specification differences, evaluation is focused on a small group of variables including U.S. visitor arrivals (visus_hi), Japanese visitor arrivals (visjp_hi), total visitor arrivals (vis_hi), hotel average daily room rate (prm_hi), personal income (yp_hi), total non-agricultural employment (eea_hi), and the Honolulu consumer price index (cpi_hon).

Rolling samples are used in the exercise except for the UHERO-model which is estimated over full sample. In this sense, UHERO-model forecasts are in sample dynamic forecasts and are expected to dominate other model forecasts. The remaining models are first fit to data over the sample period 1980Q1–1995Q4 and then re-estimated every quarter by moving the estimation ending period one quarter ahead until the end of sample 2001Q4 is reached. In doing so, regression coefficients may vary in response to enlarged data set. Every time the model is estimated, forecasts are generated for the variables of interest for one-, two-, four-, eight-quarters ahead. Pooling the forecasts together yields a set of 24 one-quarter, 23 two-quarters, 21 four-quarters, and 17 eight-quarters ahead forecasts.

Root Mean Squared Error (RMSE) is the simplest and most commonly used overall measure of forecast accuracy. It involves calculating the root of the mean of squared forecast errors in the form of:

$$RMSE = \sqrt{\frac{1}{T} \sum_{t=1}^{T} e_{t+h,t}^2}$$  (3.29)
Table 3.15 reports the one-, two-, four-, and eight-quarters ahead RMSE of the four models when applicable. It gives mixed signals on the relative performance of the four models. It appears that CointTour-model produces the best forecasts for tourism related variables such as visus.hi, visjp.hi, and prm.hi, especially at longer horizons. This is impressive considering that the UHERO-model is estimated using the full sample while CointTour-model is not. For the rest of variables where CointTour-model does not apply, the UHERO-model generally has the smallest RMSE, particularly as the forecast horizon grows. This is expected given that the UHERO-model forecasts are actually in-sample predictions.

To test whether RMSEs from alternative specifications are statistically different from each other, I use the test described in Ashley, Granger, and Schmalensee (1980). Suppose we have two competing models whose forecast errors are $e_{1t+h,t}$ and $e_{2t+h,t}$ respectively. Call one model the benchmark model and the other the competing model. We are interested in whether the RMSE of the benchmark model is significantly smaller than the RMSE of the competing model from a statistical perspective. That is, we would like to test the null hypothesis

$$H_0 : E(MSE(e_{1t+h,t}) - MSE(e_{2t+h,t})) = 0, \quad \forall t$$

versus the alternative hypothesis

$$H_0 : E(MSE(e_{1t+h,t}) - MSE(e_{2t+h,t})) = \mu > 0. \quad (3.31)$$

It can be shown that

$$MSE(e_{1t+h,t}) - MSE(e_{2t+h,t}) = [s^2(e_{1t+h,t}) - s^2(e_{2t+h,t})]$$

$$+ [m(e_{1t+h,t})^2 - m(e_{2t+h,t})^2], \quad (3.32)$$

where $s^2$ denotes sample variance and $m$ denotes sample mean. Letting

$$S_t = e_{1t+h,t} + e_{2t+h,t},$$

$$D_t = e_{1t+h,t} - e_{2t+h,t}. \quad (3.33)$$
Table 3.15: RMSE of Different Model Specifications 1996Q1–2001Q4

<table>
<thead>
<tr>
<th>Models</th>
<th>One-quarter</th>
<th>Two-quarter</th>
<th>Four-quarter</th>
<th>Eight-quarter</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>U.S. Visitor Arrivals</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>UHERO</td>
<td>0.0442</td>
<td>0.0452</td>
<td>0.0437</td>
<td>0.0466</td>
</tr>
<tr>
<td>Coint/Tour</td>
<td>0.0377 (0.85)</td>
<td>0.0379 (0.84)</td>
<td>0.0431 (0.99)</td>
<td>0.0498 (1.07)</td>
</tr>
<tr>
<td>RW</td>
<td>0.0329 (0.74)</td>
<td>0.0431 (0.95)</td>
<td>0.0646 (1.48)</td>
<td>0.0913 (1.96)</td>
</tr>
<tr>
<td><strong>Japanese Visitor Arrivals</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>UHERO</td>
<td>0.070</td>
<td>0.0790</td>
<td>0.0847</td>
<td>0.0976</td>
</tr>
<tr>
<td>Coint/Tour</td>
<td>0.0492 (0.73)</td>
<td>0.0503 (0.64)</td>
<td>0.0561 (0.66)</td>
<td>0.0595 (0.61)</td>
</tr>
<tr>
<td>RW</td>
<td>0.1002 (1.50)</td>
<td>0.1259 (1.59)</td>
<td>0.1555 (1.84)</td>
<td>0.1842 (1.89)</td>
</tr>
<tr>
<td><strong>Total Visitor Arrivals</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BVAR</td>
<td>0.0413</td>
<td>0.0566</td>
<td>0.0672</td>
<td>0.0818</td>
</tr>
<tr>
<td>UHERO</td>
<td>0.0441 (1.07)</td>
<td>0.0494 (0.87)</td>
<td>0.0489 (0.73)</td>
<td>0.0638 (0.78)</td>
</tr>
<tr>
<td>RW</td>
<td>0.0385 (0.93)</td>
<td>0.0536 (0.95)</td>
<td>0.0664 (0.99)</td>
<td>0.0682 (0.83)</td>
</tr>
<tr>
<td><strong>Average Daily Hotel Room Rate</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BVAR</td>
<td>0.0178</td>
<td>0.0208</td>
<td>0.0223</td>
<td>0.0293</td>
</tr>
<tr>
<td>UHERO</td>
<td>0.0119 (0.67)</td>
<td>0.0164 (0.79)</td>
<td>0.0217 (0.97)</td>
<td>0.0205 (0.70)</td>
</tr>
<tr>
<td>Coint/Tour</td>
<td>0.0163 (0.92)</td>
<td>0.0163 (0.78)</td>
<td>0.0163 (0.73)</td>
<td>0.0158 (0.54)</td>
</tr>
<tr>
<td>RW</td>
<td>0.0203 (1.14)</td>
<td>0.0305 (1.47)</td>
<td>0.0531 (2.39)</td>
<td>0.0919 (3.14)</td>
</tr>
<tr>
<td><strong>Total Personal Income</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BVAR</td>
<td>0.0077</td>
<td>0.0109</td>
<td>0.0155</td>
<td>0.0287</td>
</tr>
<tr>
<td>UHERO</td>
<td>0.0090 (1.24)</td>
<td>0.0088 (0.84)</td>
<td>0.0129 (0.86)</td>
<td>0.0229 (0.83)</td>
</tr>
<tr>
<td>RW</td>
<td>0.0094 (1.30)</td>
<td>0.0167 (1.60)</td>
<td>0.0332 (2.22)</td>
<td>0.0642 (2.33)</td>
</tr>
<tr>
<td><strong>Total Non-Agricultural Jobs</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BVAR</td>
<td>0.0080</td>
<td>0.0094</td>
<td>0.0144</td>
<td>0.0229</td>
</tr>
<tr>
<td>UHERO</td>
<td>0.0044 (0.55)</td>
<td>0.0045 (0.47)</td>
<td>0.0070 (0.48)</td>
<td>0.0133 (0.60)</td>
</tr>
<tr>
<td>RW</td>
<td>0.0060 (0.69)</td>
<td>0.0088 (0.92)</td>
<td>0.0157 (1.09)</td>
<td>0.0266 (1.20)</td>
</tr>
<tr>
<td><strong>Honolulu Consumer Price Index</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BVAR</td>
<td>0.0058</td>
<td>0.0095</td>
<td>0.0156</td>
<td>0.0241</td>
</tr>
<tr>
<td>UHERO</td>
<td>0.0057 (0.97)</td>
<td>0.0058 (0.62)</td>
<td>0.0079 (0.51)</td>
<td>0.0090 (0.37)</td>
</tr>
<tr>
<td>RW</td>
<td>0.0039 (0.66)</td>
<td>0.0067 (0.72)</td>
<td>0.0114 (0.75)</td>
<td>0.0207 (0.84)</td>
</tr>
</tbody>
</table>

Note: Column 1 lists the different VAR specifications; Column 2 to 5 gives the RMSE of one-, two-, four- and eight-quarter ahead forecast errors. Numbers in parentheses give the ratio of the RMSE of the associated model to the model listed in the first row. A value greater than one means that the RMSE of the given model is larger than that of the first model, indicating that the given model's forecast is less accurate than that of the first model. Italicized entries indicate the smallest RMSE in each comparison.
Equation (3.32) can be re-written as follows, even if $e_{1t+h,t}$ and $e_{2t+h,t}$ are correlated:

$$MSE(e_{1t+h,t}) - MSE(e_{2t+h,t}) = [cov(D_t, S_t)] + [m(e_{1t+h,t})^2 - m(e_{2t+h,t})^2].$$  (3.34)

From (3.34), we may conclude that the competing model outperforms the benchmark model if we can reject the joint hypothesis that $cov(D_t, S_t) = 0$ and $m(D_t) = 0$ in favor of the alternative hypothesis that both quantities are nonnegative and at least one is positive. Now consider the regression

$$D_t = \beta_1 + \beta_2 [S_t - m(S_t)] + \nu_t,$$  (3.35)

where $\nu_t$ is a zero-mean error term independent of $S_t$. The test outlined in the preceding paragraph is equivalent to testing the null hypothesis that $\beta_1 = \beta_2 = 0$ against the alternative that both are nonnegative and at least one is positive. There are several cases: 1) If $\beta_2 > 0$ and the mean errors of both forecast are of the same sign as $\beta_1$, an $F$-test is appropriate. If the $F$-test rejects, the competing model outperforms the benchmark model. 2) If the mean errors of both forecast are of the same sign but the coefficients do not have the correct signs, $\beta_1$ does not indicate the relative bias of the two forecasts. In this case, Ashley, Granger, and Schmalensee (1980) suggest using separate one-sided $t$-test. If the estimate of $\beta_2$ is significantly positive, the competing model is an improvement. Otherwise, it is not. 3) If the mean errors of the two forecasts have different signs, the test is indecisive.

In this paper, I am only interested in the comparison between the $BVAR$-model and the remaining models. To the extent that alternative model specifications overlap, we perform the AGS test on the following variables: $vis_{hi}$, $prm_{hi}$, $yp_{hi}$, $eea_{hi}$ and $cpi_{hon}$.\(^{18}\) The AGS test results are listed in table 3.16 to 3.19.\(^{19}\) Two numbers are reported in each column. The first number is the test statistic when the model listed in the first column is the benchmark model and the model listed by

\(^{18}\)The same test can be applied to other forecast accuracy evaluations, for instance, the $CointTour$-model against the $UHERO$-model.

\(^{19}\)Regression specified in equation (3.35) is corrected for $MA(h - 1)$ at $h$-step ahead for $h > 1$. 
Table 3.16: Significance Test of One-quarter Ahead RMSEs 1996Q1–2001Q4

<table>
<thead>
<tr>
<th></th>
<th>Benchmark Model</th>
<th>Competing Models</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>BVAR</td>
<td>UHERO</td>
</tr>
<tr>
<td>vis_hi</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sign mean error</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>$t(\beta_1)$</td>
<td>-2.41 / 2.41</td>
<td>n.a.</td>
</tr>
<tr>
<td>$t(\beta_2)$</td>
<td>-1.44 / 1.44</td>
<td>n.a.</td>
</tr>
<tr>
<td>Conclusion</td>
<td>not reject / reject</td>
<td>n.a.</td>
</tr>
<tr>
<td>prm_hi</td>
<td></td>
<td>+</td>
</tr>
<tr>
<td>Sign mean error</td>
<td>-</td>
<td>+</td>
</tr>
<tr>
<td>$t(\beta_1)$</td>
<td>-1.00 / 1.00</td>
<td>2.03 / -2.03</td>
</tr>
<tr>
<td>$t(\beta_2)$</td>
<td>2.59 / -2.59</td>
<td>0.72 / -0.72</td>
</tr>
<tr>
<td>Conclusion</td>
<td>? / ?</td>
<td>reject / not reject</td>
</tr>
<tr>
<td>yp_hi</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sign mean error</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>$t(\beta_1)$</td>
<td>0.02 / -0.02</td>
<td>n.a.</td>
</tr>
<tr>
<td>$t(\beta_2)$</td>
<td>0.87 / -0.87</td>
<td>n.a.</td>
</tr>
<tr>
<td>Conclusion</td>
<td>not reject / not reject</td>
<td>n.a.</td>
</tr>
<tr>
<td>eea_hi</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sign mean error</td>
<td>-</td>
<td>+</td>
</tr>
<tr>
<td>$t(\beta_1)$</td>
<td>-0.56 / 0.56</td>
<td>n.a.</td>
</tr>
<tr>
<td>$t(\beta_2)$</td>
<td>3.13 / -3.13</td>
<td>n.a.</td>
</tr>
<tr>
<td>Conclusion</td>
<td>? / ?</td>
<td>n.a.</td>
</tr>
<tr>
<td>cpi_hon</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sign mean error</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>$t(\beta_1)$</td>
<td>0.43 / -0.43</td>
<td>n.a.</td>
</tr>
<tr>
<td>$t(\beta_2)$</td>
<td>0.46 / -0.46</td>
<td>n.a.</td>
</tr>
<tr>
<td>Conclusion</td>
<td>not reject / not reject</td>
<td>n.a.</td>
</tr>
</tbody>
</table>

Note: $t(x)$, $t$-statistic of coefficient $x$. Bolded numbers indicate significance at 5% level.
Table 3.17: Significance Test of Two-quarter Ahead RMSEs 1996Q2–2001Q4

<table>
<thead>
<tr>
<th>Benchmark Model</th>
<th>Competing Models</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>vis_hi</strong></td>
<td></td>
</tr>
<tr>
<td>Sign mean error</td>
<td>n.a.</td>
</tr>
<tr>
<td>(t(\beta_1))</td>
<td>-3.49 / 3.49</td>
</tr>
<tr>
<td>(t(\beta_2))</td>
<td>1.14 / -1.14</td>
</tr>
<tr>
<td>Conclusion</td>
<td>reject / not reject</td>
</tr>
<tr>
<td><strong>prm_hi</strong></td>
<td></td>
</tr>
<tr>
<td>Sign mean error</td>
<td>n.a.</td>
</tr>
<tr>
<td>(t(\beta_1))</td>
<td>-1.01 / 1.01</td>
</tr>
<tr>
<td>(t(\beta_2))</td>
<td>2.57 / -2.57</td>
</tr>
<tr>
<td>Conclusion</td>
<td>not reject / not reject</td>
</tr>
<tr>
<td><strong>yp_hi</strong></td>
<td></td>
</tr>
<tr>
<td>Sign mean error</td>
<td>n.a.</td>
</tr>
<tr>
<td>(t(\beta_1))</td>
<td>-0.54 / 0.54</td>
</tr>
<tr>
<td>(t(\beta_2))</td>
<td>1.20 / -1.20</td>
</tr>
<tr>
<td>Conclusion</td>
<td>not reject / not reject</td>
</tr>
<tr>
<td><strong>eea_hi</strong></td>
<td></td>
</tr>
<tr>
<td>Sign mean error</td>
<td>n.a.</td>
</tr>
<tr>
<td>(t(\beta_1))</td>
<td>-0.66 / 0.66</td>
</tr>
<tr>
<td>(t(\beta_2))</td>
<td>4.98 / -4.98</td>
</tr>
<tr>
<td>Conclusion</td>
<td>not reject / not reject</td>
</tr>
<tr>
<td><strong>cpi_hon</strong></td>
<td></td>
</tr>
<tr>
<td>Sign mean error</td>
<td>n.a.</td>
</tr>
<tr>
<td>(t(\beta_1))</td>
<td>-2.35 / 2.35</td>
</tr>
<tr>
<td>(t(\beta_2))</td>
<td>3.34 / -3.34</td>
</tr>
<tr>
<td>Conclusion</td>
<td>reject / not reject</td>
</tr>
</tbody>
</table>

Note: \(t(x)\), \(t\)-statistic of coefficient \(x\). Bolded numbers indicate significance at 5% level.
Table 3.18: Significance Test of Four-quarter Ahead RMSEs 1996Q4-2001Q4

<table>
<thead>
<tr>
<th>Benchmark Model</th>
<th>UHERO</th>
<th>CointTour</th>
<th>RW</th>
</tr>
</thead>
<tbody>
<tr>
<td>vis_hi</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sign mean error</td>
<td>-</td>
<td>n.a.</td>
<td>n.a.</td>
</tr>
<tr>
<td>(t(\beta_1))</td>
<td>-4.55 / 4.55</td>
<td>n.a.</td>
<td>-5.05 / 5.05</td>
</tr>
<tr>
<td>(t(\beta_2))</td>
<td>4.56 / -4.56</td>
<td>n.a.</td>
<td>-1.65 / 1.65</td>
</tr>
<tr>
<td>Conclusion</td>
<td>reject / not reject</td>
<td>n.a.</td>
<td>not reject / not reject</td>
</tr>
<tr>
<td>prm_hi</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sign mean error</td>
<td>-</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>(t(\beta_1))</td>
<td>-3.00 / 3.00</td>
<td>-0.27 / 0.27</td>
<td>-17.96 / 17.96</td>
</tr>
<tr>
<td>(t(\beta_2))</td>
<td>0.50 / -0.50</td>
<td>1.75 / -1.75</td>
<td>-2.33 / 2.33</td>
</tr>
<tr>
<td>Conclusion</td>
<td>? / ?</td>
<td>not reject / not reject</td>
<td>? / ?</td>
</tr>
<tr>
<td>yp_hi</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sign mean error</td>
<td>-</td>
<td>-</td>
<td>+</td>
</tr>
<tr>
<td>(t(\beta_1))</td>
<td>1.26 / -1.26</td>
<td>n.a.</td>
<td>-4.89 / 4.89</td>
</tr>
<tr>
<td>(t(\beta_2))</td>
<td>1.04 / -1.04</td>
<td>n.a.</td>
<td>-0.53 / 0.53</td>
</tr>
<tr>
<td>Conclusion</td>
<td>not reject / not reject</td>
<td>n.a.</td>
<td>? / ?</td>
</tr>
<tr>
<td>eea_hi</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sign mean error</td>
<td>+</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>(t(\beta_1))</td>
<td>-0.23 / 0.23</td>
<td>n.a.</td>
<td>-3.38 / 3.38</td>
</tr>
<tr>
<td>(t(\beta_2))</td>
<td>8.62 / -8.62</td>
<td>n.a.</td>
<td>1.39 / -1.39</td>
</tr>
<tr>
<td>Conclusion</td>
<td>reject / not reject</td>
<td>n.a.</td>
<td>not reject / not reject</td>
</tr>
<tr>
<td>cpi_hon</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sign mean error</td>
<td>-</td>
<td>n.a.</td>
<td>+</td>
</tr>
<tr>
<td>(t(\beta_1))</td>
<td>-3.51 / 3.51</td>
<td>n.a.</td>
<td>-7.11 / 7.11</td>
</tr>
<tr>
<td>(t(\beta_2))</td>
<td>3.25 / -3.25</td>
<td>n.a.</td>
<td>3.40 / -3.40</td>
</tr>
<tr>
<td>Conclusion</td>
<td>reject / not reject</td>
<td>n.a.</td>
<td>? / ?</td>
</tr>
</tbody>
</table>

Note: \(t(x)\), t-statistic of coefficient \(x\). Bolded numbers indicate significance at 5% level.
Table 3.19: Significance Test of Eight-quarter Ahead RMSEs 1997Q4–2001Q4

\[ H_0 : \beta_1 = 0 = \beta_2 : \text{Equation (35)} \]

<table>
<thead>
<tr>
<th>Benchmark Model</th>
<th>Competing Models</th>
<th>BVAR</th>
<th>UHERO</th>
<th>CointTour</th>
<th>RW</th>
</tr>
</thead>
<tbody>
<tr>
<td>( vis_{hi} )</td>
<td>Sign mean error</td>
<td>-12.87 / 12.87</td>
<td>n.a.</td>
<td>-15.40 / 15.40</td>
<td></td>
</tr>
<tr>
<td>( t(\beta_1) )</td>
<td>n.a.</td>
<td>2.54 / -2.54</td>
<td>n.a.</td>
<td>0.005 / -0.005</td>
<td></td>
</tr>
<tr>
<td>Conclusion</td>
<td>reject / not reject</td>
<td>n.a.</td>
<td>reject / not reject</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( prm_{hi} )</td>
<td>Sign mean error</td>
<td>-7.47 / 7.47</td>
<td>-0.71 / 0.71</td>
<td>-19.82 / 19.82</td>
<td></td>
</tr>
<tr>
<td>( t(\beta_1) )</td>
<td>2.52 / -2.52</td>
<td>3.78 / -3.78</td>
<td>-4.22 / 4.22</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Conclusion</td>
<td>? / ?</td>
<td>reject / not reject</td>
<td>? / ?</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( yp_{hi} )</td>
<td>Sign mean error</td>
<td>-4.95 / 4.95</td>
<td>n.a.</td>
<td>-7.68 / 7.68</td>
<td></td>
</tr>
<tr>
<td>( t(\beta_1) )</td>
<td>2.32 / -2.32</td>
<td>n.a.</td>
<td>-2.09 / 2.09</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Conclusion</td>
<td>reject / not reject</td>
<td>n.a.</td>
<td>not reject / reject</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( eea_{hi} )</td>
<td>Sign mean error</td>
<td>0.94 / -0.94</td>
<td>n.a.</td>
<td>-4.76 / 4.76</td>
<td></td>
</tr>
<tr>
<td>( t(\beta_1) )</td>
<td>3.49 / -3.49</td>
<td>n.a.</td>
<td>0.81 / -0.81</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Conclusion</td>
<td>reject / not reject</td>
<td>n.a.</td>
<td>not reject / not reject</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( cpi_{hon} )</td>
<td>Sign mean error</td>
<td>-4.45 / 4.45</td>
<td>n.a.</td>
<td>-4.88 / 4.88</td>
<td></td>
</tr>
<tr>
<td>( t(\beta_1) )</td>
<td>2.19 / -2.19</td>
<td>n.a.</td>
<td>1.57 / -1.57</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Conclusion</td>
<td>reject / not reject</td>
<td>n.a.</td>
<td>not reject / not reject</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: \( t(x) \), t-statistic of coefficient x. Bolded numbers indicate significance at 5% level.
the corresponding column is the competing model. The second number gives the test statistic when the roles of benchmark and competing models are switched. For instance, in the first block in table 3.16, -2.41 and -1.44 are the $\beta_1$ and $\beta_2$ estimates when $BVAR-model$ is the benchmark model and $UHERO-model$ is the competing model, whereas 2.41 and 1.44 are the $\beta_1$ and $\beta_2$ estimates when $UHERO-model$ is the benchmark model and $BVAR-model$ is the competing model.

The test results in tables 3.16 to 3.19 to some extent confirm the RMSE comparisons in table 3.15. At one-quarter ahead, the AGS test indicates that $RW-model$ produces the smallest RMSE for $vis_hi$ among all models. For $prm_hi$, there is only one case where the AGS test is decisive, which shows that $CointTour-model$ produces a smaller RMSE than $BVAR-model$. At two-quarters ahead, AGS test rejects in two cases and it seems that the $UHERO-model$ is the best model for $vis_hi$ and $cpi_hon$. At four-quarters ahead, the AGS test indicates that $UHERO-model$ is the best model for three variables: $vis_hi$, $eea_hi$ and $cpi_hon$. At eight-quarters ahead, the AGS test shows that $UHERO-model$ produces the most accurate forecast for all variables except $prm_hi$, which is best forecasted by $Coint-model$. Apart from these, the $RW-model$ is clearly outperformed by $BVAR-model$ for $vis_hi$ and $yp_hi$. In general, the $UHERO-model$ dominates because its forecasts are in-sample forecasts while forecasts from other models are out-of-sample dynamic forecasts.

3.8 Conclusion

Regional econometric modeling and forecasting have long been the heart of successful economic analysis, policy evaluation, and public planning. Various methods are found in the literature, ranging from traditional large-scale theory-driven macro models to the more recent less theory dependent VAR specifications. The BVAR approach proposed by Litterman (1980) offers a solution to the over-parameterization problem in unrestricted VAR specifications and is an effective alternative to regional modeling and forecasting.

The rising popularity of nonstructural regional models is also explained by
data limitations at the subnational levels. Income-side gross state product (GSP) data are available only at annual frequency with significant lags and there is no expenditure-side GSP data at all. As such, traditional income and product accounts theory-driven macro models are largely precluded.

This paper represents the first attempt to model a regional economy via different BVAR blocks. In doing so, the model accounts for both the intra-actions within the region and the inter-actions of the region with external driving forces. The formation of BVAR blocks follows standard income and product account table structure. Proxy variables are found in high frequency income and employment, tax base, and export activity data where direct measurements are not available. In terms of prior specifications, the model incorporates not only traditional priors on individual variables but also linear combination priors such as the sums of coefficients prior and the dummy initial observation prior.

Forecasts from the proposed pseudo income and product account model are compared to those from a typical regional macroeconometric model—the forecasting system maintained by the University of Hawaii Economic Research Organization (UHERO-model). It seems that the BVAR forecasting system is outperformed by the UHERO-model. This is almost certainly due to the fact that forecasts from the UHERO-model are in-sample while those from the BVAR forecasting system are out-of-sample dynamic forecasts.

In light of the seemingly under-performing BVAR system, it is worthwhile to level the playing field and use out-of-sample forecasts for the UHERO-model. The UHERO-model is a large system containing hundreds of equations. Estimation of the model using a rolling sample requires significant efforts and is left for a future paper. Some other extensions of this work may include expanding the prior search range as priors selected fall on the bound in many cases. It is also possible to expand the whole system to include sector details following Patridge and Rickman (1998) and use input-output coefficients as informative priors.
Bibliography


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