The Aggregate of Elasticities or the Elasticity of the Aggregates: U.S. Trade in Services

Jaime Marquez[1]
Federal Reserve Board
Washington DC, 20051
United States
jaime.marquez@frb.gov

January 21, 2005

[1] I would like to thank Neil Ericsson, David Hendry, Cathy Mann for their detailed comments. The calculations are based on PcGets; see Hendry and Krolzig (2001). The views in this paper are solely the responsibility of the authors and should not be interpreted as reflecting the views of the Board of Governors of the Federal Reserve System or of any other person associated with the Federal Reserve System.

Abstract

I use the automated search algorithm to address practical issues that arise in estimating income and price elasticities for U.S. trade in services: specification of dynamics, specification of the search strategy, simultaneity biases, and aggregation biases. Specifically, starting from a general, autoregressive distributed lag formulation, I use automated specification algorithms to obtain a specific formulation. I assess simultaneity biases by applying OLS, IV, and FIML. I assess aggregation biases by comparing the aggregate of the elasticities to the elasticity of the aggregate. Ignoring these considerations results in a formulation that cannot explain the divergence of service and merchandise balances.

When computers first replaced hand calculations for computing regressions, I remember complaints that 'no one will really understand the process'; yet econometrics could not have progressed without computers. Similarly, with automatic selection. Granger and Hendry (2004, p. 16)

Right now, econometrics is in its infancy in considering this very wide class of problems in automated specification searches, model construction, validation and inference. While consensus is unlikely in the consideration of the many methodological issues that arise in this process, increasing reliance on computerization and some degree of automation in estimation and inference seem certain to be part of the future of econometrics. Phillips (2004, p. 14)

1 Introduction

The history of econometrics offers numerous instances where the introduction of a technical development gives rise to research in other areas.[1] The technical development that I examine here is that of automated selection algorithms. Specifically, I use the automated search algorithm developed by Krolzig and Hendry (2001) to address practical issues that arise in estimating income and price elasticities for U.S. trade in services.

Two facts motivate my interest in this line of inquiry. The first one is that, after being virtually identical for nearly fifty years, the balances of services and merchandise, began diverging since 1976 (figure 1). Does this divergence imply that the forces determining trade in merchandise differ from the forces determining trade in services? Or does it mean that the forces determining both types of trade are the same except that they operate with different intensities? These questions bring me to the second fact: the coexistence of a growing surplus in services and a growing deficit in merchandise trade has not been studied, much less explained, in the literature. Indeed, papers modeling U.S. trade in services are rare, especially if contrasted to the case of the voluminous literature documenting income and price elasticities for U.S. trade in merchandise.[2]

The maintained prior in this paper is that the imperfect substitute model is relevant for explaining trade in services. This prior is the same one maintained by analyses explaining merchandise trade. Such a parallel would be unremarkable if were not for the observation that the balances of service and merchandise have diverged since 1976 (figure 1). Indeed, if the imperfect substitute model is going to explain divergent trends in services and merchandise trade balances, then one ought to expect for a significant difference in the associated elasticity estimates. Otherwise, the model could not account for these divergences.

Finding a difference in estimates, significant as it might be, is not enough, however.

[1] See Morgan (1992) for a history of econometrics.

[2] Two key studies modeling services are Reeve (2001) and Deardorf et al. (2001). Marquez (2002) reviews the literature on estimating income and price responses in merchandise trade.

The difference in estimates must be such that it can explain the divergence of balances. Thus I focus on the one finding that studies of U.S. trade in merchandise have in common: the asymmetry in the estimated income elasticities or, more specifically, that U.S. imports are more income elastic than U.S. exports. This asymmetry, noted first by Houthakker and Magee in 1969, suggests that if every country were to exhibit the same growth rate, then U.S. imports would increase faster than U.S. exports. U.S. growth during the 1990s exceeded that of her trading partners and resulted in a significant deterioration of the U.S. merchandise balance. The question, then, is whether the income elasticity of aggregate exports of services is greater than the income elasticity of aggregate imports of services. Failure to find this reversed asymmetry in income elasticities would question the usefulness of the results reported here.

Section 2 describes the structure of automated specification algorithms and brings out practical modeling issues: the specification of dynamics, the specification of the search strategy, the potential for simultaneity biases, and the potential for aggregation biases. Specifically, I start with a general, autoregressive distributed lag formulation and then apply automated specification algorithms to obtain a specific formulation. To examine the potential for simultaneity biases I apply three types of estimators that differ in the amount of information they embody: ordinary least squares, instrumental variables, and full information maximum likelihood. To address the question of aggregation bias, I estimate income and price elasticities for aggregate exports and imports of services as well as for their four components. I then compare the aggregate of the estimated elasticities from the components to the elasticity of the aggregate.

That these considerations matter in principle for modeling international trade is well known (Goldstein and Khan, 1985). What is less well known is how important they are in practice and that is what I do here. The results reported in section 4 indicate that dynamic specification, search strategy, and biases from simultaneity and aggregation are important enough to change one's understanding of the forces giving rise to figure 1. Indeed, ignoring these four considerations results in an empirical model that, though congruent with the data, is at odds with the divergence of service and merchandise balances.

2 Empirical Formulation

2.1 Econometric Specification

I start by giving the benefit of the doubt to the imperfect substitute model explaining movements in trade in terms of movements in income and relative prices assuming constant elasticities.[3] The associated autoregressive distributed lag specification for exports of the

[3] Log-linear formulations are the most common formulations; see Golsdtein and Khan (1985) and Marquez (2002) for reviews of the literature, including the choice of formulations.

ith type of services is

$$(1-\theta_{1i}(L))\ln x_{it} = \theta_{0i} + \theta_{2i}(L)\ln(\frac{P_{xit}}{P_t^*}) + \theta_{3i}(L)\ln y_t^* + u_{xit}, \quad (1)$$

where x_i represents exports of services, in real terms, of the *ith* category, y^* denotes foreign real GDP, P_{xi} denotes the dollar export price of the *ith* category of services, P^* denotes the foreign GDP deflator expressed in U.S. dollars, $\theta_{ki}(L) = \sum_{\ell=0}^{n_x} \theta_{kij} L^j$ $(k > 0)$ where L is the lag operator, u_{xit} is a random disturbance, and n_x is the number of lags, common to all the variables. The long-run income elasticity is $\theta_{iy} = \frac{\theta_{3i}(1)}{1-\theta_{1i}(1)} > 0$; the long-run price elasticity is $\theta_{ip} = \frac{\theta_{2i}(1)}{1-\theta_{1i}(1)} < 0$. The corresponding formulation for aggregate export services is

$$(1-\theta_1(L))\ln x_t = \theta_0 + \theta_2(L)\ln(\frac{P_{xt}}{P_t^*}) + \theta_3(L)\ln y_t^* + u_{xt}, \quad (2)$$

where x represents aggregate exports of services in real terms, P_{xt} denotes the dollar export price of aggregate services, $\theta_i(L) = \sum_{\ell=0}^{n_x} \theta_{ij} L^j$, and u_{xt} is a random disturbance. The long-run income elasticity is $\theta_y = \frac{\theta_3(1)}{1-\theta_1(1)} > 0$ and the long-run price elasticity is $\theta_p = \frac{\theta_{2i}(1)}{1-\theta_{1i}(1)} < 0$.

The specification for imports of the *ith* type of services is

$$(1-\phi_{1i}(L))\ln m_{it} = \phi_{0i} + \phi_{2i}(L)\ln(\frac{P_{mit}}{P_t}) + \phi_{3i}(L)\ln y_t + u_{mit}, \quad (3)$$

where m_i represents imports of services, in real terms, of the *ith* type of service, y denotes real GDP, P_{mi} denotes the dollar import price of services, P denotes the U.S. GDP deflator, u_{mit} is a random disturbance, $\phi_{ki}(L) = \sum_{\ell=0}^{n_m} \phi_{kij} L^j$, and n_m is the number of lags, common to all the variables. The long-run income elasticity is $\phi_{iy} = \frac{\phi_{3i}(1)}{1-\phi_{1i}(1)} > 0$ and the long-run price elasticity is $\phi_{ip} = \frac{\phi_{2i}(1)}{1-\phi_{1i}(1)} < 0$. The corresponding specification for aggregate imports of services is

$$(1-\phi_1(L))\ln m_t = \phi_0 + \phi_2(L)\ln(\frac{P_{mt}}{P_t}) + \phi_3(L)\ln y_t + u_{mt}, \quad (4)$$

where m represents aggregate imports of services in real terms, P_{mt} denotes the dollar import price of aggregate services, $\phi(L)$ is a polynomial in the lag operator L, and u_{mi} is a random disturbance. The long-run income elasticity of the aggregate is $\phi_y = \frac{\phi_3(1)}{1-\phi_1(1)}$ and the long-run price elasticity is $\phi_p = \frac{\phi_2(1)}{1-\phi_1(1)} < 0$.

2.2 Aggregation Biases

To assess the importance of aggregation, I compare the aggregate of elasticities to the elasticity of the aggregate. For exports, the aggregate of income elasticities is

$$\theta_{yt}^{d} = \sum_{i} \mu_{it} \cdot \theta_{iy}, \tag{5}$$

where μ_{it} is the export share of the ith type of service exports. The elasticity of the aggregate exports, from equation (2), is θ_y. For imports, the aggregate of income elasticities is

$$\phi_{yt}^{d} = \sum_{i} \omega_{it} \cdot \phi_{iy}, \tag{6}$$

where ω_{it} is the import share of the ith type of service imports. The elasticity of the aggregate exports, equation (4), is ϕ_y.

There are several reasons why the aggregate of income elasticities might differ from the income elasticity of the aggregate. First, the aggregate of elasticities may change in response to changes in the composition of services, a feature documented below. The elasticity of the aggregate, θ_y on the other hand, assumes away these compositional changes. Second, the dynamic responses differ across the various types of services and there is no reason to expect that the dynamics of the components are the same as the dynamics of the aggregate. Third, there is no reason to expect that market structures for the various types of services are the same as the market structure for the aggregate. Thus the importance of simultaneity for the aggregate and for the components could differ, a difference that translates into an aggregation bias. The questions of interest are, then, whether the aggregate of estimates is sufficiently different from θ_{yt}, and if so which one should be used in practical applications?

2.3 Data Sources and Definitions

I disaggregate the aggregate data for services into their four components: travel, fares, other transportation, and other private services.[4] Figure 2 shows the share of these components in total exports of services; figure 3 shows the corresponding shares in total import of services. Overall, the data exhibit changes in the composition of services over time, a feature motivating the interest in quantifying aggregation biases.

Data for travel covers expenditures on goods and services by U.S. travelers abroad and by foreign visitors to the United States.[5] The items that are covered are food, lodging, recreation, gifts, and local transportation. Exports of travel services were, until 1996, the largest type of service exports with a share in excess of 30 percent (figure 2). Imports of

[4] All of the data for services, both in current and constant prices come from the Survey of Current Business prepared by the Bureau of Economic Analysis (BEA). The components for Defense and Royalties are excluded as they do not involve arm's length negotioations. These components represent a small share of the aggregate services.

[5] A Traveler is a person that stays for a period less than one year in a country in which the person is not a resident.

travel services are the largest component of imports of services with a share well in excess of 35 percent of total imports of services (figure 3).

Data for fares consist of fares paid by foreign travelers to U.S. carriers (exports) and of fares paid by U.S. residents to foreign carriers and foreign cruise operators (imports). The export share of fares has been declining since 1987 and has not exceeded 10 percent of total exports of services (figure 2). The import share of fares has been increasing since 1987 but has not exceeded 15 percent of total imports of services.

Data for transportation covers freight services for ocean, air, rail (Canada and Mexico); expenses by shippers abroad in foreign ports; payments to foreign residents for vessel charters, aircraft rentals, freight car rentals. The export share of transportation services has declined from 20 percent to 10 percent (figure 2); the corresponding import share declines from 25 percent in 1987 to 15 percent in 2001 (figure 3).

Data for exports of other private services consist of receipts for education, financial services, insurance, telecommunications, business, and other.[6] The export share of other private services has steadily increased reaching nearly 45 percent in 2001 (figure 2). Data for import of other private services consist of payments by U.S. residents on the same six categories: education, financial services, insurance, telecommunications, business, and other. The import share of Other Private Services has steadily increased from 22 percent to nearly 30 percent by 2001 (figure 3). Notice the large swing in the third quarter of 2001 due to the manner in which expenditures on insurance are computed: Premiums minus losses recovered, which were large due to the 9/11 attacks on the United States.

To measure U.S. economic activity I use BEA's chain weighted measure of GDP in constant prices. To measure foreign economic activity, I use a geometric average of real GDP of 36 countries:[7]

$$y_t^* = \prod_j {Y_{jt}}^{\gamma_{jt}}, \ \ \sum_j \gamma_{jt} = 1, \tag{7}$$

where Y_j is the real GDP of the jth country, as an index and γ_{jt} is the share of country j in U.S. exports of services.

I measure the relative import price of the ith category as $\frac{P_{mit}}{P_t}$ where P_{mi} is the chain weighted price index for imports of the ith category and P is the chain weighted price for GDP; data for both prices come from the Bureau of Economic Analysis. I measure the

[6] Education: expenditures by foreign students in the United States.

Financial services: commissions and transactions fees associated with purchases of U.S. securities.

Telecommnications: telephone services, telex, e-mails, management of data networks and satellites' information.

Business: receipts for services provided in accounting, auditing, bookkeeping, advertising, computer and data processing, engineering, architectural, legal, consulting, medical services, performing arts, sport events.

Other: The items are film and tape rentals, earnings of U.S. residents temporarily employed abroad, expenditures of foreign residents employed temporarily in the United States, expenditures by international organizations in the United States.

[7] All of the OECD (23 excluding the United States), China, and selected countries from Latin America and East Asia.

relative price of exports of the ith category as $\frac{P_{xit}}{P_t^*}$ where P_{xit} is the chain weighted export price index for the ith category of services, which is provided by the BEA, and P^* is the foreign GDP deflator in US$. In the absence of public data for this price deflator, I measure it as

$$P_t^* = \prod_j (PY_{jt} \cdot E_{\$/j,t})^{\gamma_{jt}}, \sum_j \gamma_{jt} = 1, \tag{8}$$

where $E_{\$/j}$ is the price of the jth foreign currency in terms of US$ and PY_j is the GDP deflator for the jth country in local currency.

3 Automated Selection Algorithm

If equations (1)-(4) are treated as representing general unrestricted models, then the task of specification involves obtaining a parsimonious specification by "eliminating" statistically insignificant variables. Eliminating insignificant variables as such is not a new strategy. What is new here is the sole reliance on *PcGets'* computer-automated algorithm, developed by Hendry and Krolzig (2001), to exclude redundant variables.[8] This reliance has two advantages. First, their automated search algorith is exhaustive because it considers all of the statistically valid specifications. Second, their algorithm adjusts the significance levels for statistical tests to recognize the joint nature of model specification and parameter estimation. Finally, and key to a practitioner, each step in the process of automated search can be replicated at once. Despite these advantages, the current release of *PcGets* functions only for limited-information estimators.

Algorithm *PcGets'* computer-automated algorithm combines least squares with a selection strategy that is implemented in four stages:[9]

1. Estimate the parameters of an unrestricted formulation–equation (1) for example–and test for congruency (white-noise residuals and parameter constancy).

2. Implement multiple reduction paths simultaneously. One reduction path could get started by excluding the least significant variable whereas another reduction path could get initiated by excluding a block of variables that are statistically insignificant.

3. Test whether the specification from a reduction path is congruent. If it is, then implement another round of reductions and test for congruency; continue this process until the specification violates congruency. In that case, the algorithm selects the immediately prior specification and labels it *Final model*.

[8] For an exposition of these issues see Hendry and Krolzig (2003).

[9] I use Package version 1.02 of PcGets as installed in an IBM ThinkPad A31 with 512 mb of memory using Windows 2000 Professional. I use PcGets' default settings.

4. Collect the Final models from various reduction paths and applying encompassing tests to them. The specification that encompasses all others becomes the *Specific model*. If there is no single encompassing model, then the algorithm forms a "union" model using the variables from all of the Final models and re-starts the specification search from step (2). If this strategy fails to yield a single Specific model, then the algorithm applies three information criteria (Akaike, Schwarz, and Hannan-Quinn) to the Final models and selects the one that minimizes all these criteria; that model becomes the Specific model.[10] Otherwise, the algorithm fails to find a Specific model.

Strategies Automated search strategies are subject to two types of errors: to keep irrelevant variables or to exclude relevant variables. *PcGets* allows the user to specify which type of error is deemed more important. If the cost of excluding a relevant variable is deemed higher than the cost of retaining an irrelevant variable, then the specification strategy will err on the side of retaining more variables in the specification; this strategy is labeled as "Liberal." Alternatively, if the user deems the cost of including irrelevant variables as being higher than the cost of excluding relevant variables, then the specification strategy will err on the side of excluding relevant variables; this strategy is labeled "Conservative." In the absence of an objective function to assess these costs, I reports results for both strategies.

3.1 Estimation Methods

I estimate the parameters of equations (1)-(4) using three methods: ordinary least squares (OLS), instrumental variables (IV), and full-information maximum likelihood. For instruments I use the lagged ratio of U.S. claims on foreigners relative to U.S. GDP, the lagged ratio of U.S. liabilities to foreigners to U.S. GDP, the price of domestic services, contemporaneous and lagged. I have not evaluated the results to alternative instruments.

Applying FIML involves specifying a system of equations that includes specifications for relative prices and economic activity. One convenient way of developing the system is to create a vector autoregression model and then estimate the parameters using the Johansen FIML procedure.

The system used to explain exports, foreign economic activity, and relative export prices, all variables expressed in logarithms, is

$$\Delta z_{xt} = \kappa_x + \sum_{\ell=1}^{n_x} \Gamma_{x\ell} \Delta z_{x,t-\ell} + \Gamma_{xo} z_{x,t-1} + \epsilon_{xt}, \epsilon_{xt} \sim NI(0, \Omega_x), \tag{9}$$

where $z'_{xt} = (x_t \; y_t^* \; rpx_t)$; κ_x is a 3x1 vector of intercepts, Γ_{xi} is a 3x3 matrix of coefficients

[10] There is no guarantee that reliance on these three criteria will yield a unique model. In the event that the application of these criteria yields more than one model, the user specifies a criteria ranking to settle the conflict. In this paper, I use the Akaike Information Criterion.

for short-run interrelations; and

$$\Gamma_{xo} = \alpha_x \beta_x' = \begin{pmatrix} \alpha_{x11} & ... & \alpha_{x13} \\ ... & ... & ... \\ \alpha_{x31} & ... & \alpha_{x33} \end{pmatrix} \begin{pmatrix} \beta_{x11} & ... & \beta_{x31} \\ ... & ... & ... \\ \beta_{x13} & ... & \beta_{x33} \end{pmatrix}. \tag{10}$$

The elements of α_x measure the speed of adjustment and are known as loading coefficients; the vector $(\beta_{x1i}\ \beta_{x2i}\ \beta_{x3i}) = \beta_{xi}'$ characterizes the ith long-run relation among x_t, y_t^*, and rpx_t. For example, the relation associated with β_{x1}' is

$$x = -\left(\frac{\beta_{x21}}{\beta_{x11}}\right) y^* - \left(\frac{\beta_{x31}}{\beta_{x11}}\right) rpx. \tag{11}$$

The system used to explain imports, economic activity, and relative import prices, all variables expressed in logarithms,

$$\Delta z_{mt} = \kappa_m + \sum_{\ell=1}^{n_m} \Gamma_{mi} \Delta z_{m,t-\ell} + \Gamma_{mo} z_{m,t-1} + \epsilon_{mt}, \epsilon_{mt} \sim NI(0, \Omega_m), \tag{12}$$

where $z_{mt}' = (m_t\ y_t\ rpm_t)$; κ_m is a 3x1 vector of intercepts, Γ_i is a 3x3 matrix of coefficients for short-run interrelations; and

$$\Gamma_{mo} = \alpha_m \beta_m' = \begin{pmatrix} \alpha_{m11} & ... & \alpha_{m13} \\ ... & ... & ... \\ \alpha_{m31} & ... & \alpha_{m33} \end{pmatrix} \begin{pmatrix} \beta_{m11} & ... & \beta_{m31} \\ ... & ... & ... \\ \beta_{m13} & ... & \beta_{mx33} \end{pmatrix}. \tag{13}$$

The elements of α_m measure the speed of adjustment and are known as loading coefficients; the vector $(\beta_{m1i}\ \beta_{m2i}\ \beta_{m3i}) = \beta_{mi}'$ characterizes the ith long-run relation among m_t, y_t, and rpm_t. For example, the relation associated with β_{m1}' is

$$m = -\left(\frac{\beta_{m21}}{\beta_{m11}}\right) y - \left(\frac{\beta_{m31}}{\beta_{m11}}\right) rpm, \tag{14}$$

where $rpm = \log(\frac{P_{mt}}{P_t})$.

4 Estimation Results

4.1 Limited Information

For estimation, I consider two methods: ordinary least squares (OLS) and instrumental variables (IV), three lag lenghts (4, 6, 8 quarters) and three search strategies: no-search, liberal, and conservative. This estimation design translates into 18 specifications for each type of export and import of services. The sample consists of quarterly observations from 1987 to 2001.

Figures 4-8 show the estimated income and price elasticities; tables A1-A10 in the appendix indicate whether the residuals from these specifications exhibit normality, serial independence, and conditional homoskedasticity. These tables also include key statistics comparing the general and the specific formulation: standard errors, number of parameters, maximum lag in the specification.

To keep the discussion manageable, I focus on three questions: What are the consequences of a change in the search strategy given the estimation method and lag-length? What are the effects of a change in the estimation method given the lag-length and search strategy? Finally, what happens to the estimates in response to a change in lag-length given estimation method and search strategy? I evaluate the economic significance of the results in section 3.2 below.

Aggregate Exports (figure 4, top panel) Reliance on automated specification suggests that aggregate service exports are income elastic and price inelastic. However, changes in lag lengths, estimation method, and search strategy change the point estimates in every instance except OLS with four lags. For example, IV estimation using 8 lags and no lags suggests no income effects whereas relying on automated search yields an income elasticity of 1.7.

Aggregate Imports (figure 4, bottom panel) Automated search is responsible for the difference between implausible estimates (no search) and plausible estimates (automated search) for the case of 8 lags. Otherwise, income elasticities are above one and price elasticities are greater than one (in absolute value). The OLS estimates are not sensitive to changes in the number of lags and are, in general, unaffected by the adoption of an automated strategy. In contrast, the IV estimates are quite sensitive to lag length: general formulations with more than four lags yield positive (IV) price elasticities.

Exports of Other Private Services (figure 5, top panel) In general, these exports are income elastic and price inelastic. Automated search matters in every instance except OLS with eight lags. Specifically, the only instances of negative price elasticities involve combining instrumental variables and automated search: without these two features, the results do not support the conventional imperfect substitute model. Finally, the choice of search strategy matters a lot. Specifically, the three instances where the best-fitting model is an autoregressive formulation stem from relying on a conservative strategy.

Imports of Other Private Services (figure 5, bottom panel) In general, these imports are income elastic and price elastic. Automated search matters for every configuration of estimation method and lag length; the choice of automated specification strategy is less relevant. For example, the IV estimate of the price elasticity with 8 lags and no search is positive whereas reliance on automated search yields a negative price elasticity. Simultaneity also matters: price elasticities based on OLS are much smaller (in absolute value) than the corresponding IV estimates.

Fares Exports (figure 6, top panel) The consideration of alternative lag lengths, estimation methods, automated specification strategies does not yield elasticity estimates helpful to predicting external imbalances in terms of movements in income and relative prices. Specifically, for one-third of the final specifications, automated search algorithms suggest that the best model for export fares is an autoregressive formulation. The sole exception to this pattern is the specification using 8 lags with no search. For this case, the income elasticity is a little less than a half and the price elasticity is about minus one.

Fare Imports (figure 6, bottom panel) In general, these imports are income elastic and price elastic. For specifications using less than eight lags, the estimated income and price elasticities show a narrow range of variation across estimation methods and search strategies: simultaneity biases are small and reliance on automated search makes little difference for inference. For eight lags, however, changes in either the choice of strategy or the estimation method have large effects on the point estimates.

Exports of Transportation Services (figure 7, top panel) In general, these exports are income elastic and price inelastic. This pattern is largely invariant to changes in lag lengths or in estimation methods. However, changes in the search strategy have sizeable effects on the price elasticity, regardless of whether one uses OLS or instrumental variables. For example, the OLS estimate of the price elasticity based on 4 lags and no search is -0.6 (insignificant) whereas reliance on a conservative automated search lowers the price elasticity to -0.11 but makes it statistically significant.

Imports of Transportation Services (figure 7, bottom panel) In general, these imports are income elastic but the estimate of the price inelasticity is particularly sensitive to changes in design. For example, the only case of negative price elasticities are found for the case of six lags with OLS and automated specification search. Again, in the absence of such algorithm, the inference would be that the United States does not have suitable substitutes for foreign transportation services.

Travel Exports (figure 8, top panel) In general, these exports are income elastic and price inelastic. For estimates based on four lags, the estimates show a narrow range of variation across estimation methods and search strategies. These results suggest that simultaneity biases are small and that reliance on automated search make little difference for inference. The exception is the case of IV estimation with six lags: reliance on automated search yields either a time-series formulation or one with a positive price elasticity.

Travel Imports (figure 8, bottom panel) In general, these imports are income elastic and price elastic. Moreover, the estimates show a narrow range of variation across the estimation methods, lag lenghts, and the search strategies. This narrow range is the more interesting given that simplification of the general model with eight lags yields a specific formulation also with eight lags (see table A-10).

4.2 Full Information

I implement the Johansen FIML procedure using several lag-lenghts and, for each of the resulting systems, I test whether the vector of residuals exhibits joint normality, serial independence, and conditional homoskedasticity. Also, I report the number of cointegration vectors and the loading coefficient. These test results are shown in tables A1-A10 in the appendix.

I assess the economic implications of alternative estimation methods and aggregation schemes by comparing the FIML estimates to those based on OLS and IV. For each of these last two, I select the specification with the smallest standard error out of the class of congruent specifications. Table 1 shows the FIML estimates for each category of export and import of services as well as the estimates for the corresponding trade aggregates.

The results reveal that the price elasticity for each type of exports is smaller (in absolute terms) than the price elasticity for the corresponding type of imports. In other words, U.S. services do not face good substitutes abroad and U.S. exporters can raise their prices without fearing a significant loss of sales. Alternatively, foreign exporters face good U.S. substitutes and a fairly limited ability in raising prices. Income elasticities for exports and imports generally exceed one; the exception is exports of transportation services. The results also indicate that income elasticities for exports are greater than the corresponding income elasticities for imports, except for Fares.

From an econometric standpoint, the most significant result is that, for both income and price elasticities, the difference between IV and OLS estimates is negligible when compared to the difference between IV and FIML estimates. In other words, what matters is how one handles the simultaneity: just using instruments gives the appearance of "the results being comparable to the OLS estimates," a common finding in the literature.

4.3 Practical Implications

4.3.1 Aggregation and Simultaneity Biases

To assess the magnitude of the aggregation bias, I compare the estimates for the aggregate of elasticities to the elasticity of the aggregates. Overall, the results reveal that aggregation biases are present and that their magnitude depends on the estimation method.

For exports (figures 9-10), the results indicate that the income elasticity of the aggregate equation is always lower than the aggregate of the income elasticities from the disaggregated equations. In other words, aggregation is biasing the income elasticity downwards, though the magnitude and significance of the biases is sensitive to the estimation method: the aggregation bias is significant only for FIML. For the price elasticity, the results indicate that the estimate based on the aggregate equation is significantly lower (in absolute terms) than the estimate based on the aggregation of price elasticities for service-specific categories.

For imports (figures 11-12), the results indicate that the income elasticity of the aggregate equation is higher than the aggregate of the income elasticities from the disaggregated equations. In other words, aggregation is biasing the income elasticity upwards, though the magnitude and significance of the biases is sensitive to the estimation method. For the price elasticity, the results indicate that the estimate based on the aggregate equation is significantly different from the estimate based on the aggregation of service-specific categories, though the direction of the bias is sensitive to the estimation method.

4.3.2 Do the results explain the merchandise-service balance divergence?

To assess whether the elasticity estimates for services obtained here differ from the estimates for merchandise obtained elsewhere, I focus the asymmetry in the estimated income elasticities. For U.S. trade in merchandise, 35 years of empirical work find that U.S. imports are more income elastic than U.S. exports. The question, then, is whether the response of aggregate exports of services to changes in foreign income is greater than the response of aggregate imports of services to U.S. income. Failure to find this reversed asymmetry in income elasticities would question the usefulness of the results reported here.

Figure 13 compares the estimated income elasticities for aggregate exports and aggregate services. I report estimates for the three estimation methods and for the two alternatives for measuring the aggregate response (the aggregate of elasticities and the elasticity of the aggregates). The results indicate that the aggregate of the export elasticities is significantly higher than the aggregate of the import elasticities. This finding constitutes a statistically significant reversal of the asymmetry of income elasticities found in merchandise trade. Though the magnitude of the gap is sensitive to the estimation method, its presence and statistical significance are not. The results also reveal that, without exception, the elasticity estimates based on aggregate data do not exhibit such a reversal: Disaggregation is central to accounting for the divergence in the U.S. merchandise and services balances.

What is the role played by automated search in this conclusion? Addressing this question involves re-computing the asymmetry of income elasticities associated with estimates not using automated search. Table 2 reports two income elasticities for each type of service trade and estimator: the one used in figure 13 and the one estimated without search. For exports, the difference in point estimates between search and no search is small. For imports, however, abstracting from search has two effects: an increase in the point estimate and an increase in the estimate's standard error. The line in figure 13 labeled "estimate without search" is the aggregate of income elasticities using no-search estimates. The results suggest that the aggregate of no-search elasticities for imports is quite close to that of exports. In other words, no search means no asymmetry reversal: automated search is central to accounting for the divergence in the U.S. merchandise and services balances.

Is the reversal of the asymmetry solely a statistical result or are there economic reasons that could explain it? One should expect for trade in services to differ in several important ways from trade in merchandise and for these differences to yield elasticities for service trade that differ from the elasticities for merchandise trade. First, the provision of a service is tailored to the individual demanding that service and thus one should expect a greater scope for diversification: Insurance policies are more diverse than oil barrels. Second, services are not storable and their provision involves shorter delays than the provision of merchandise trade. Third, advances in information technology (IT) in the United States may have resulted in a comparative advantage in the provision of services. Specifically, Mann (2003) notes, IT advances have facilitated the tasks of creating, exploiting, and managing information and all of these tasks are about the provision of services. These features make U.S. service exports "superior" products and thus are associated with income elasticities much greater than one–that is, the reversal of the asymmetry in income elasticities.

5 Conclusions

The main conclusion is that one can use the imperfect substitute model as a viable tool for explaining the divergence in service and merchandise balances of the United States. Central to this conclusion are the recognition of traditional econometric issues – aggregation and simultaneity biases– and the adoption of a new econometric development–automated search. Without this recognition and this adoption, the imperfect substitute model used in the last 35 years cannot explain the divergence in U.S. external balances.

I realize that finding support for a modeling approach is not the same a ruling out the alternatives. Nevertheless, finding that the "imperfect-substitute" paradigm cannot be ruled out a priori means that alternative paradigms, if supported by the data, would have to provide a better explanation than the one offered here.

References

[1] Deardorff, A., S. Hymans, R. Stern, and C. Xiang, 2001, "Forecasting U.S. Trade in Services," in R. Stern, ed., *Services in the International Economy: Measurement and Modeling, Sector and Country Studies, and Issues in the WTO Services Negotiations*, University of Michigan Press, 53-81.

[2] Goldstein, M. and M. Khan, 1985, "Income and Price Effects in Foreign Trade," in R. Jones and P. Kenen (eds.), *Handbook of International Economics*, vol 2, pp. 1041-1105.

[3] Granger, C. and D. H. Hendry, 2004, "A Dialogue Concerning a New Instruemtn for Econometric Modeling," *Econometric Theory*, forthcoming.

[4] Hendry, D. F. and H. Krolzig, 2001, *Automatic Econometric Model Selection Using PcGets*, London: Timberlake.

[5] Hendry, D. F. and H. Krolzig, 2003, "New Developments in Automatic General-to-Specific Modeling," in B. Stigum (2003), *Econometrics and the Philosophy of Economics*, Princeton University Press.

[6] Houthakker, H. and S. Magee, 1969, "Income and Price Elasticities in World Trade," *Review of Economics and Statistics*, 51, 111-125.

[7] Mann, C., 2003, "Globalization of IT Services and White Collar Jobs: The Next Wave of Productivity Growth," *International Economics Policy Briefs* No. PB03-11, Washington, DC: Institute of International Economics.

[8] Marquez, J., 2002, *Estimating Trade Elasticities*, Dordrecht: Kluwer Academic Publishers.

[9] Morgan, M., 1992, *The History of Econometric Ideas.* New York : Cambridge University Press, 1992

[10] Phillips, P., 2004, "Automated Discovery in Econometrics," *Cowles Foundation Discussion Paper* No. 1469, New Haven, Yale University.

[11] Reeve, T., 2001, "Trade in Services," Federal Reserve Board, mimeo.

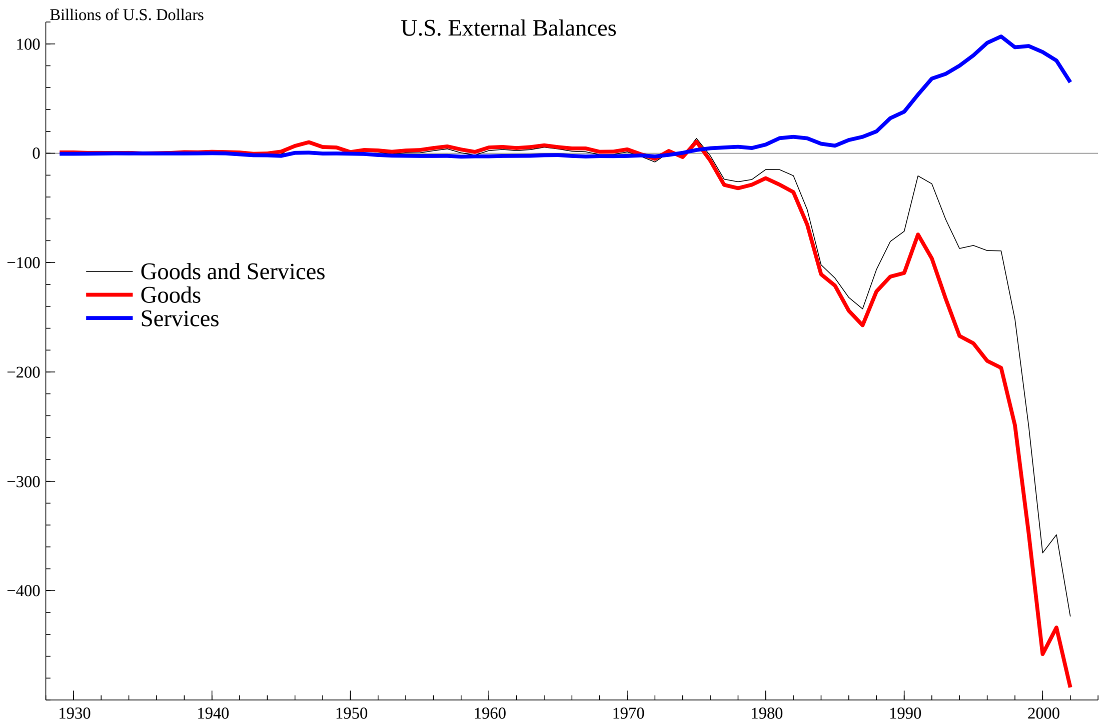


Figure 1

The measure of services reported differs from the balance on investment income which also has shown a surplus.

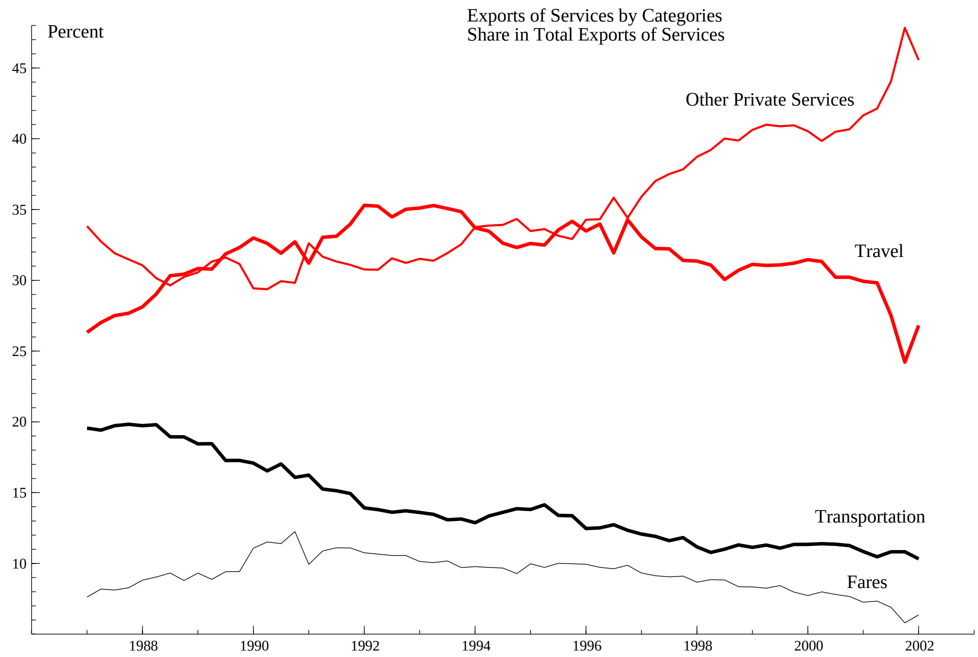


Figure 2

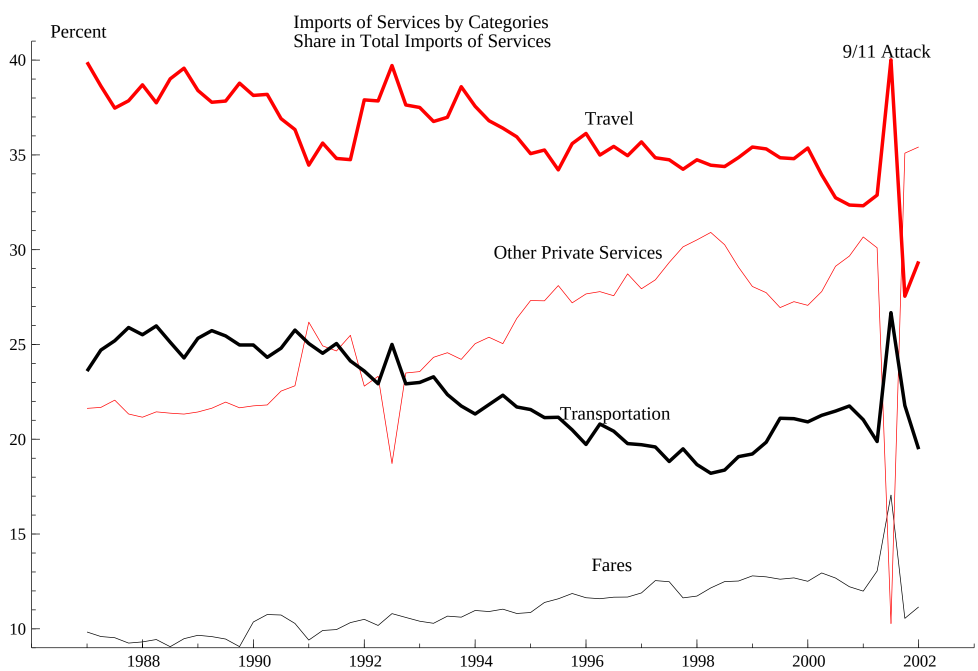
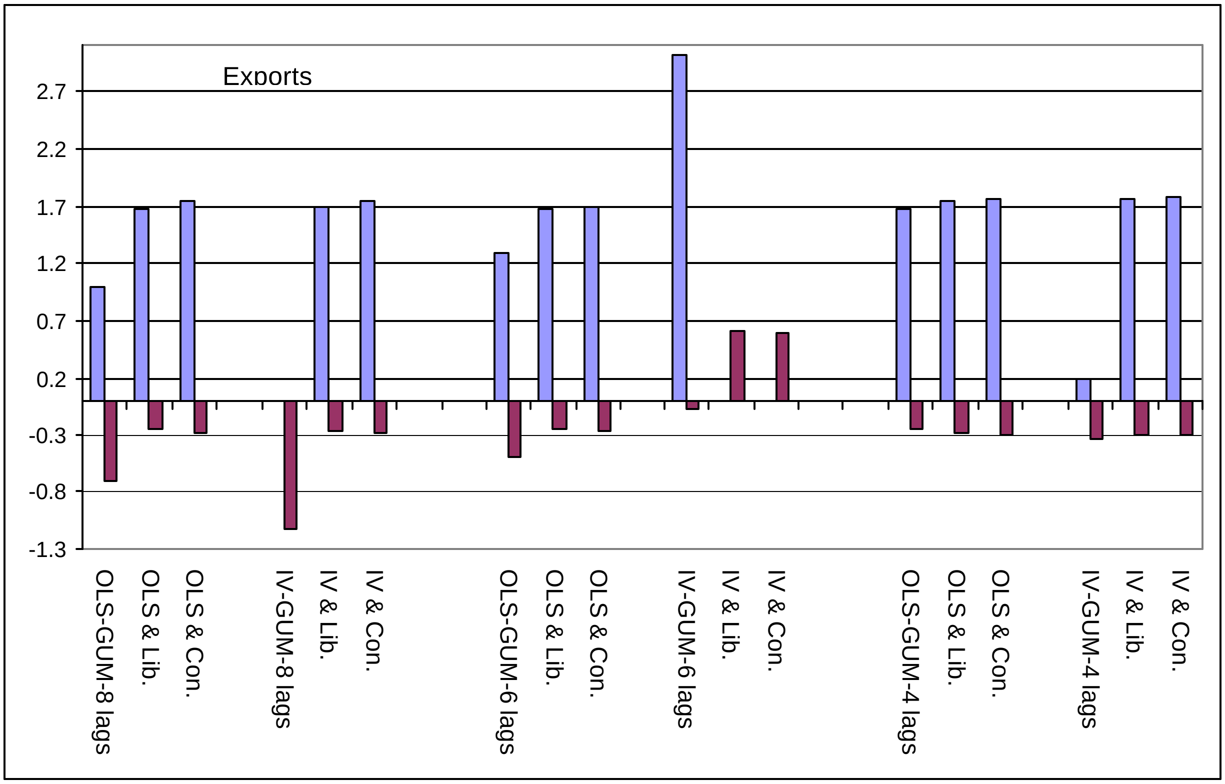
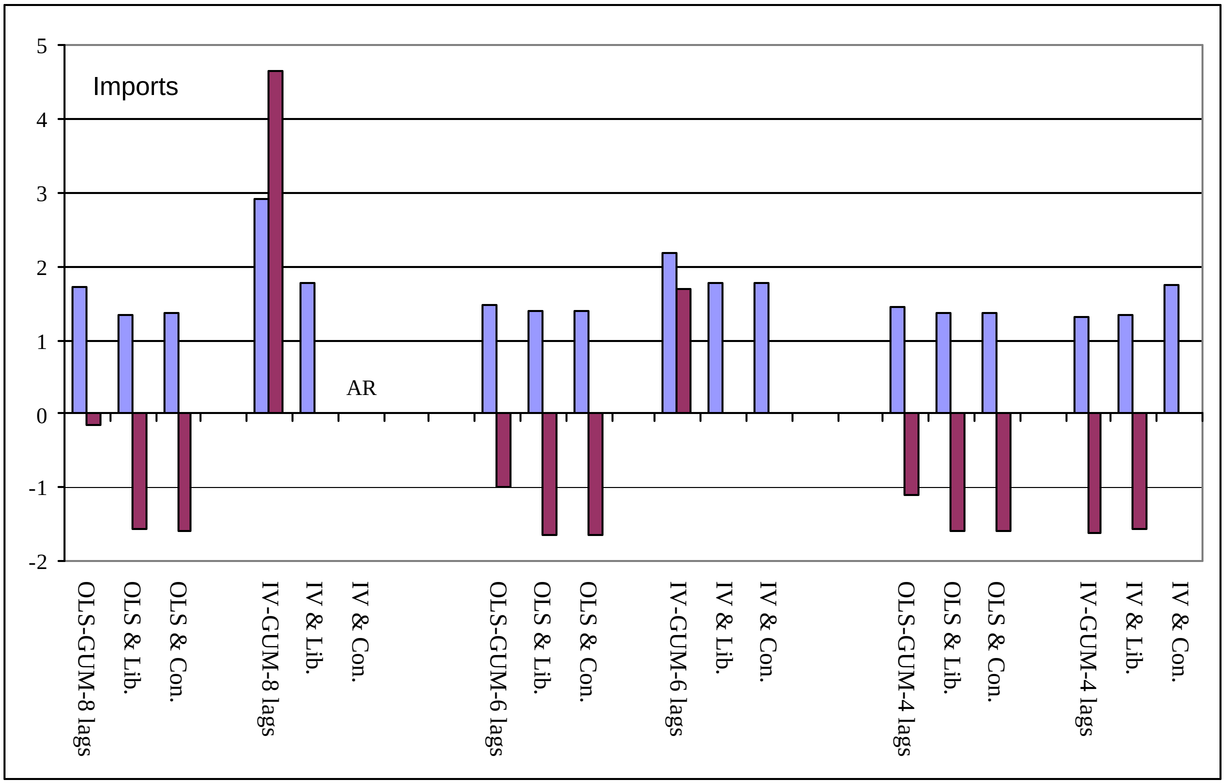


Figure 3

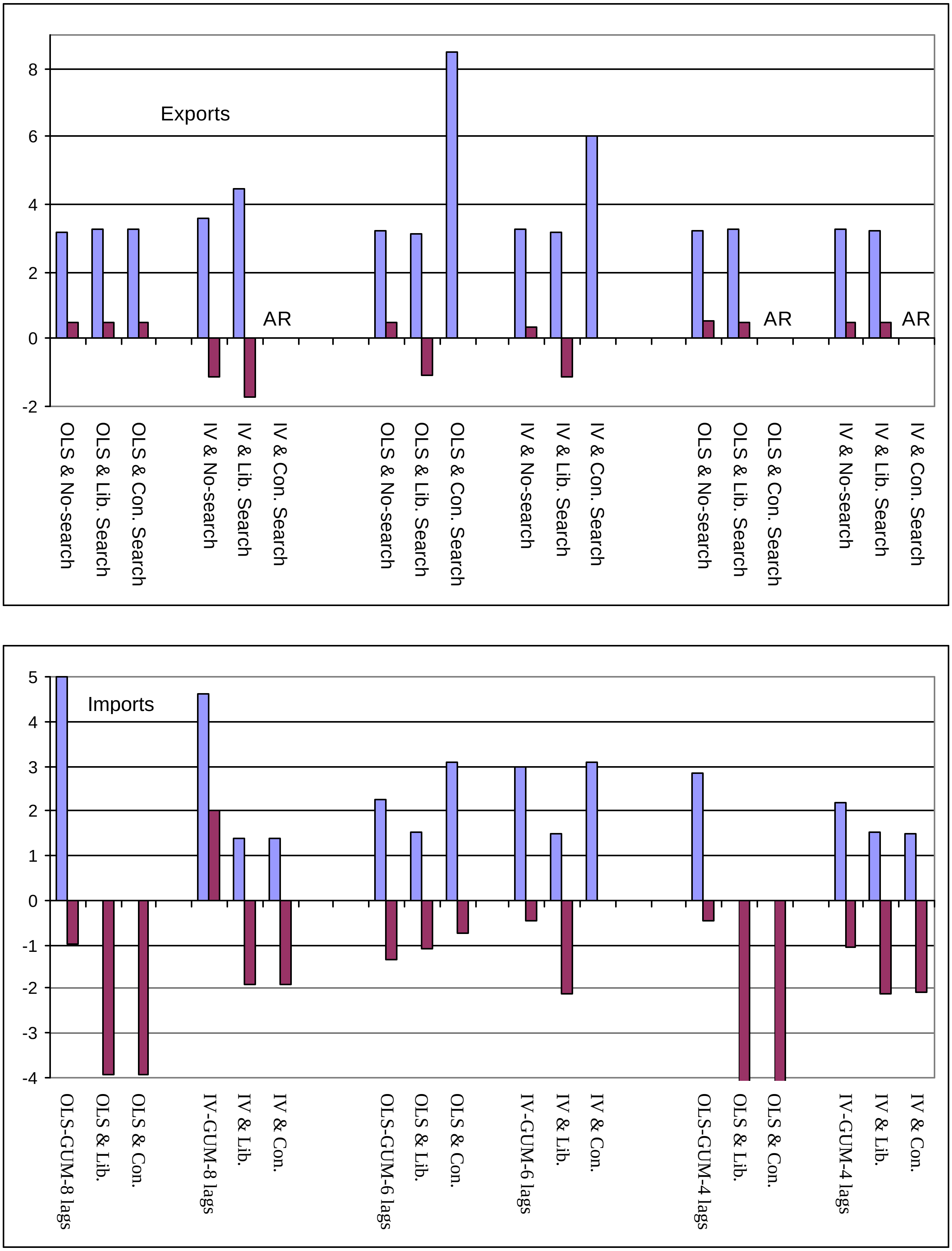
Figure 4: Income and Price Elasticities for Aggregate Exports and Imports of Services – 1987-2001
Alternative Estimation Methods and Automated Specification Algorithms





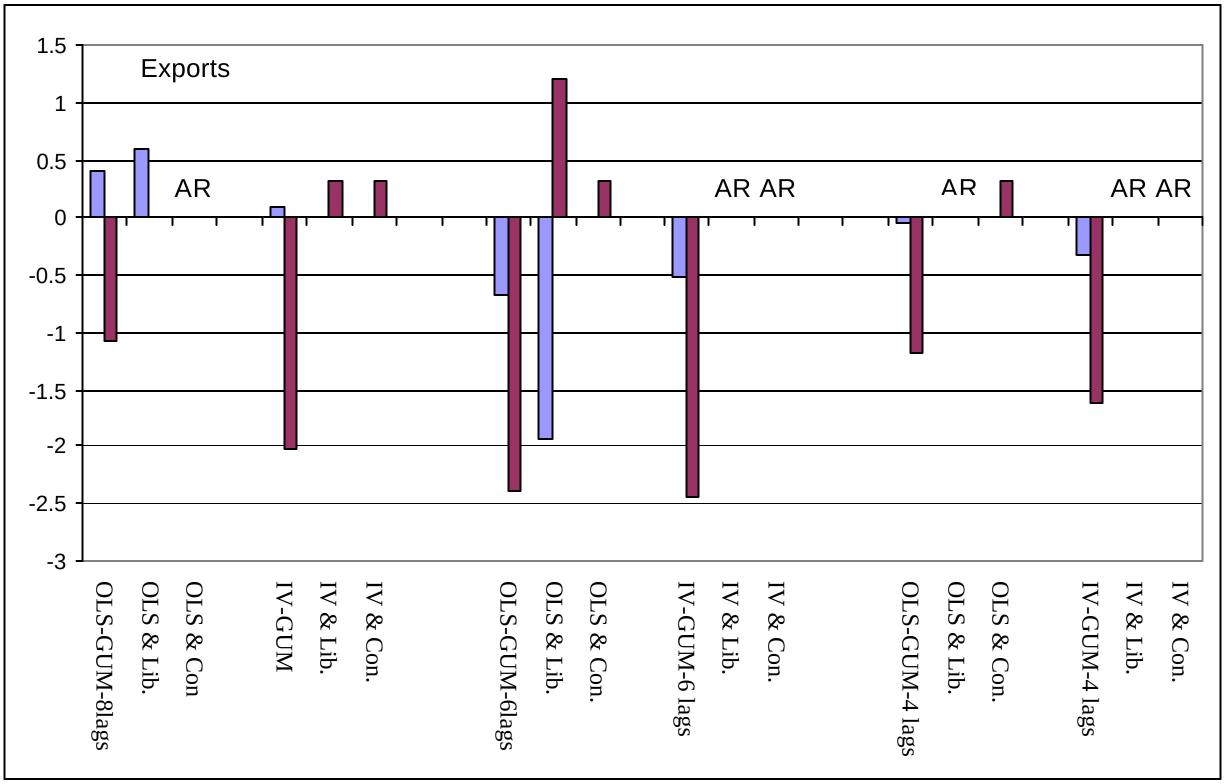
AR: Autoregressive Specification
GUM: General Unrestricted Model
Lib:. Liberal specification strategy
Con.: Conservative specification strategy

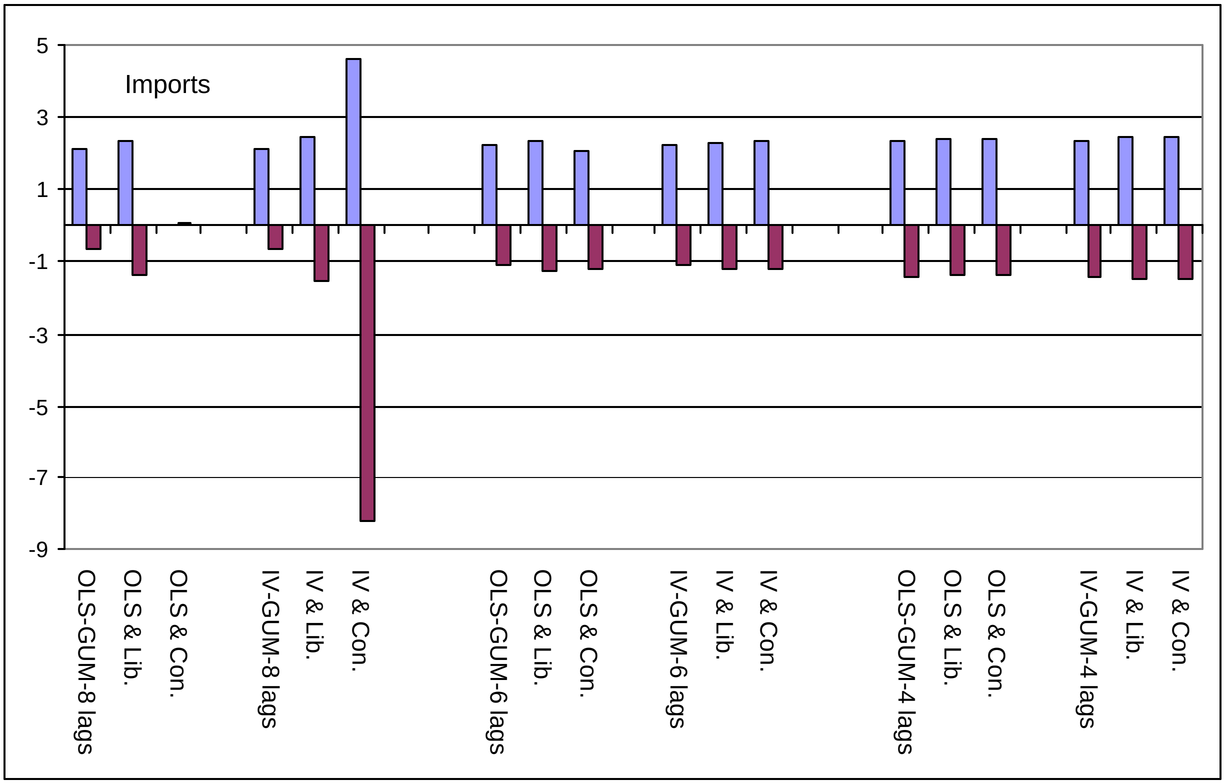
Figure 5: Income and Price Elasticities for Exports and Imports of Other Private Services – 1987-2001
Alternative Estimation Methods and Automated Specification Algorithms



AR: Autoregressive Specification
GUM: General Unrestricted Model
Lib.: Liberal specification strategy
Con.: Conservative specification strategy

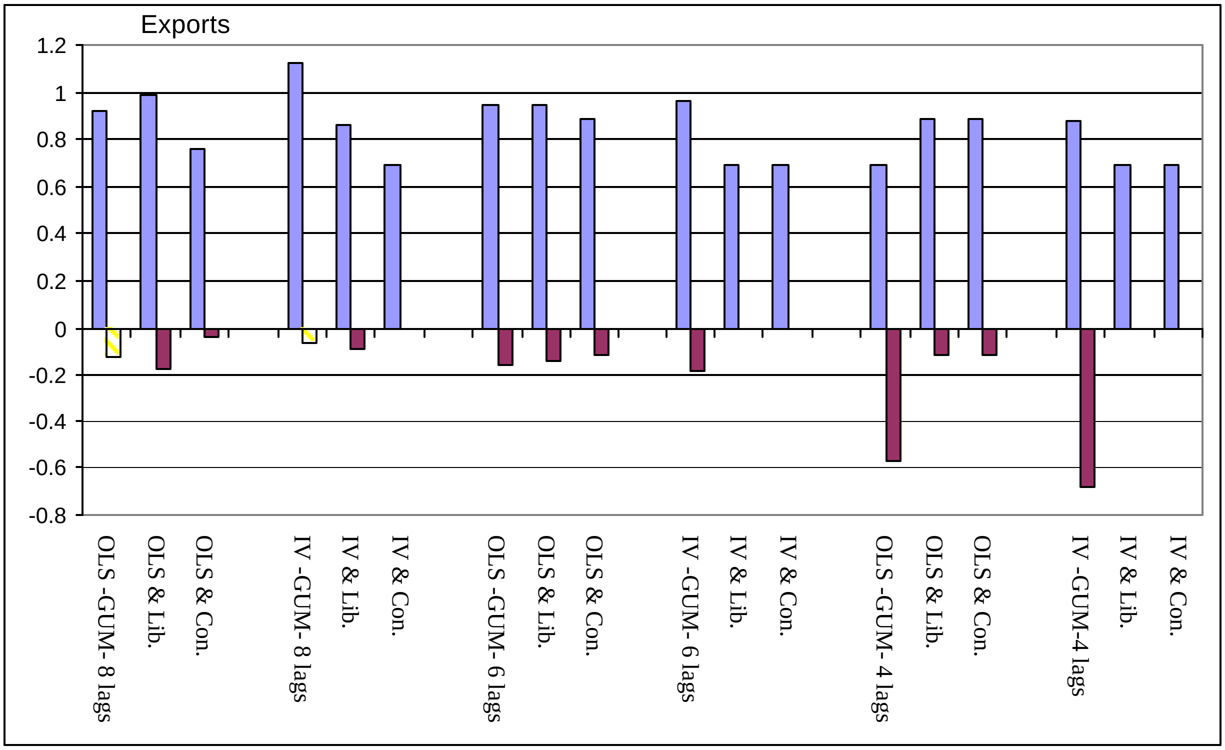
Figure 6: Income and Price Elasticities for Aggregate Exports and Imports of Fare Services – 1987-2001
Alternative Estimation Methods and Automated Specification Algorithms

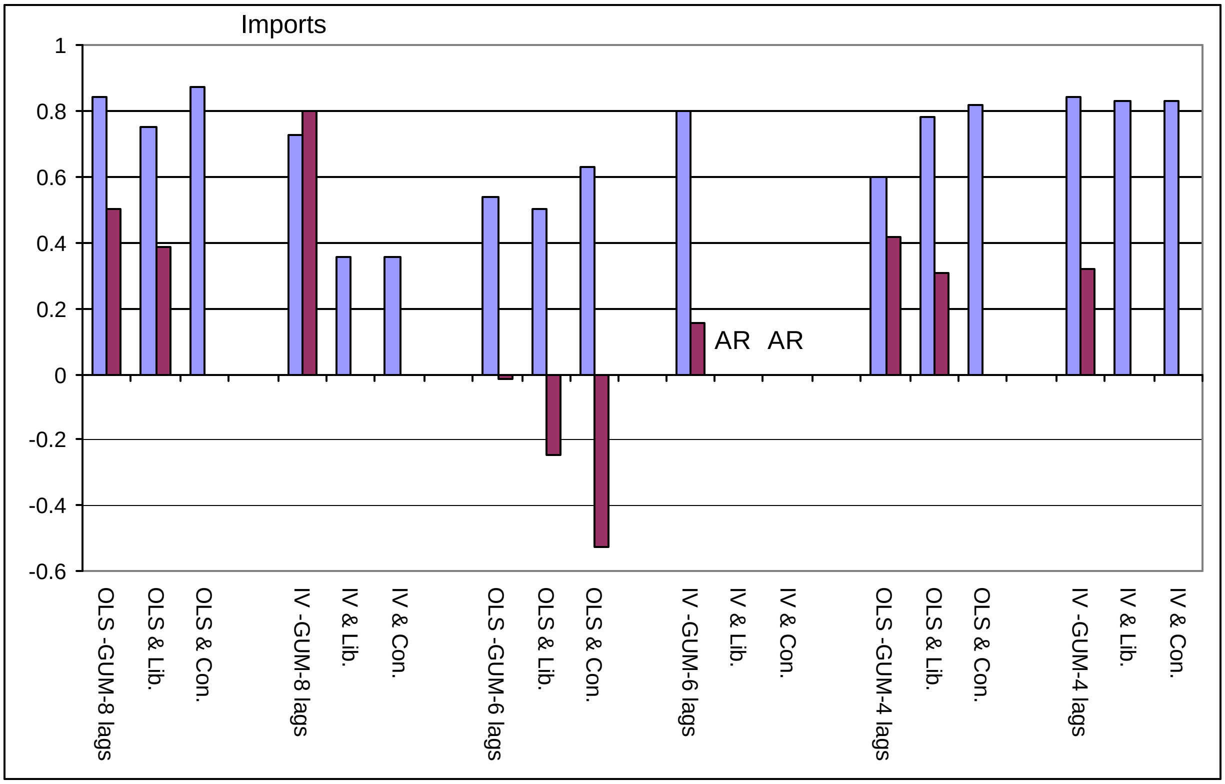




AR: Autoregressive Specification
GUM: General Unrestricted Model
Lib.: Liberal specification strategy
Con.: Conservative specification strategy

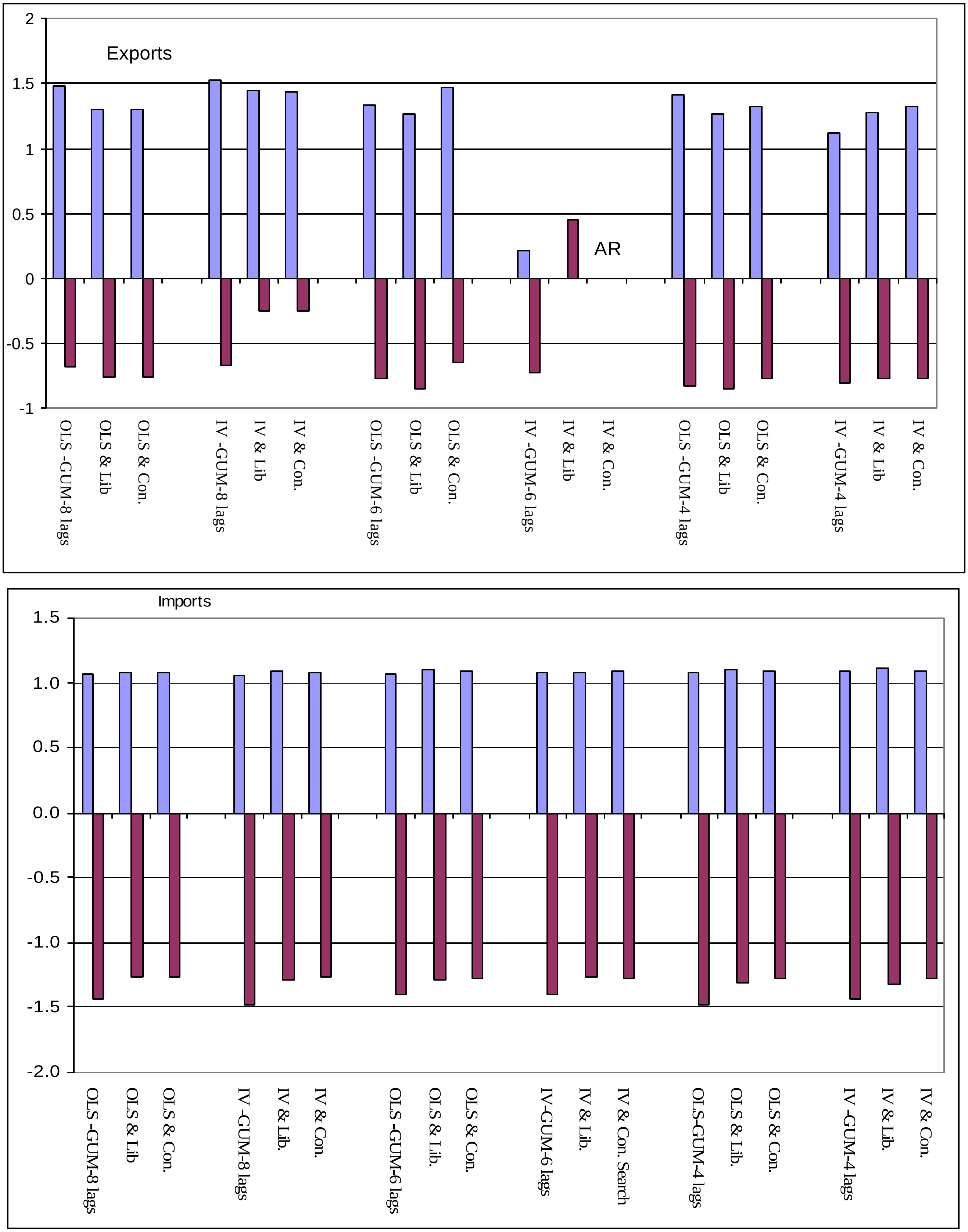
Figure 7: Income and Price Elasticities for Aggregate Exports and Imports of Transportation Services – 1987-2001
Alternative Estimation Methods and Automated Specification Algorithms





AR: Autoregressive Specification
GUM: General Unrestricted Model
Lib.: Liberal specification strategy
Con.: Conservative specification strategy

Figure 8: Income and Price Elasticities for Aggregate Exports and Imports of Travel Services – 1987-2001
Alternative Estimation Methods and Automated Specification Algorithms



AR: Autoregressive Specification
GUM: General Unrestricted Model
Lib.: Liberal specification strategy
Con.: Conservative specification strategy

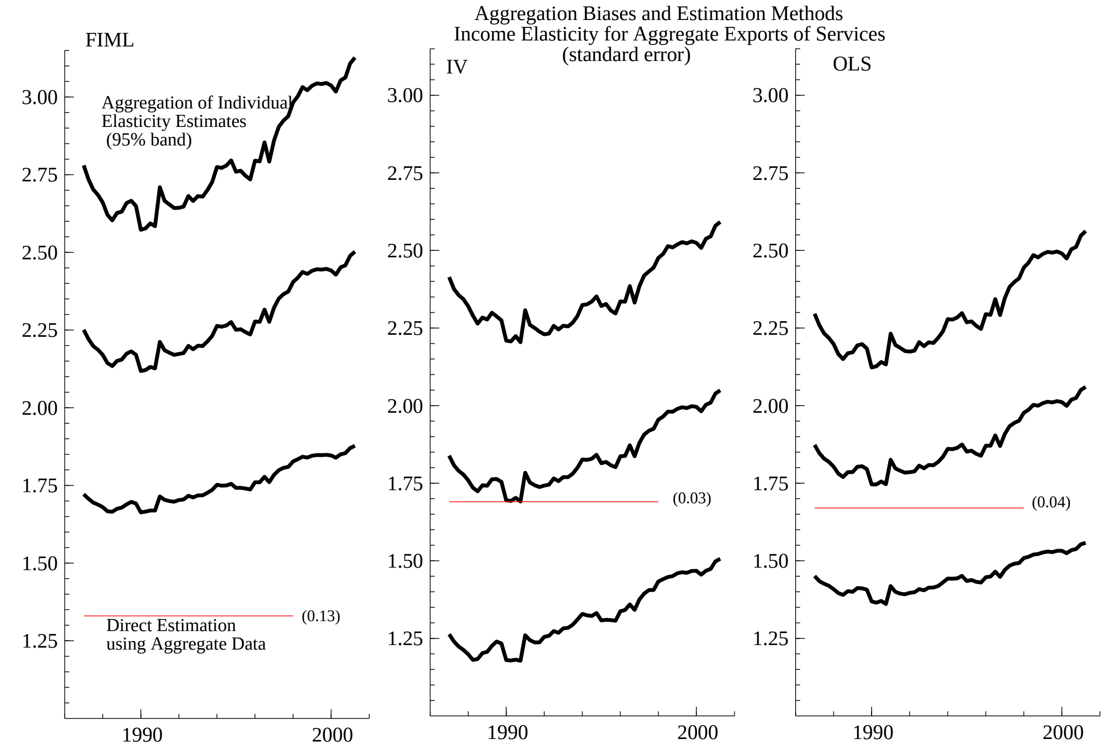


Figure 9

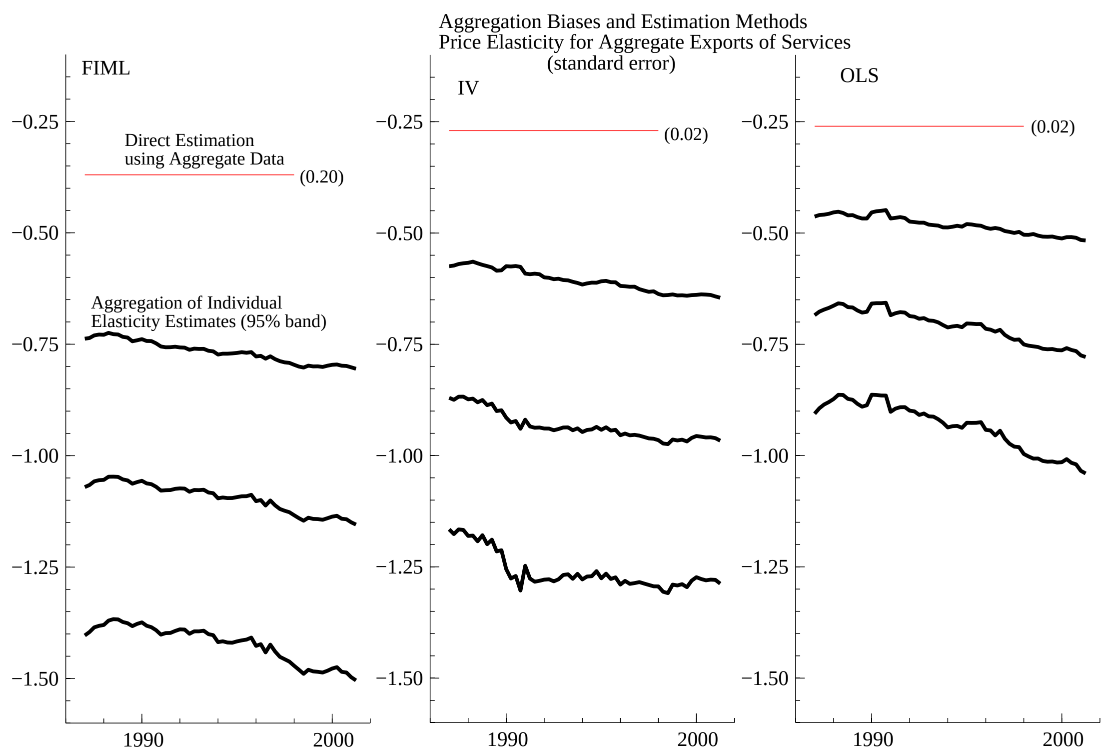


Figure 10

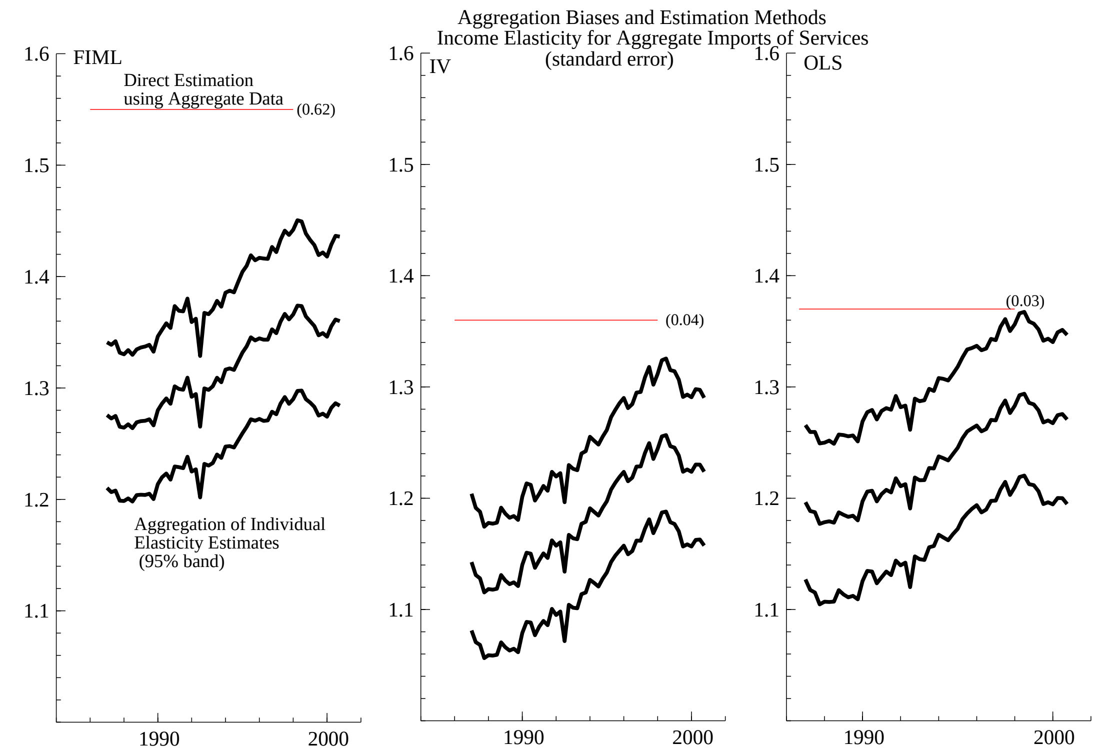


Figure 11

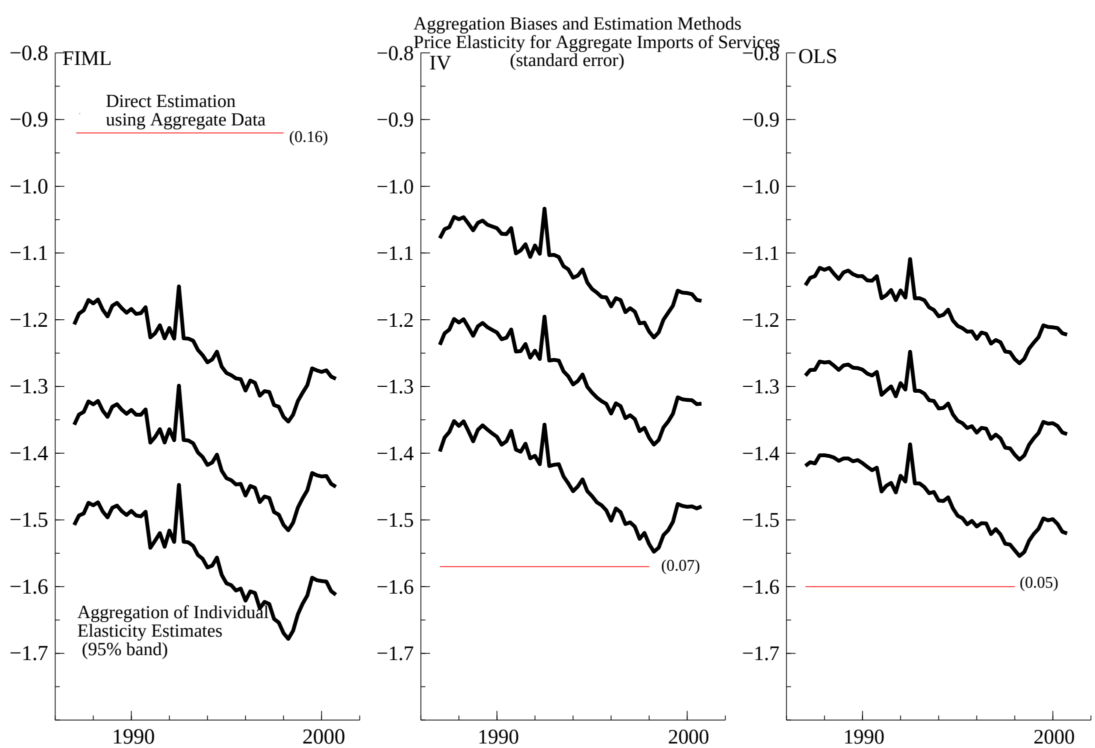
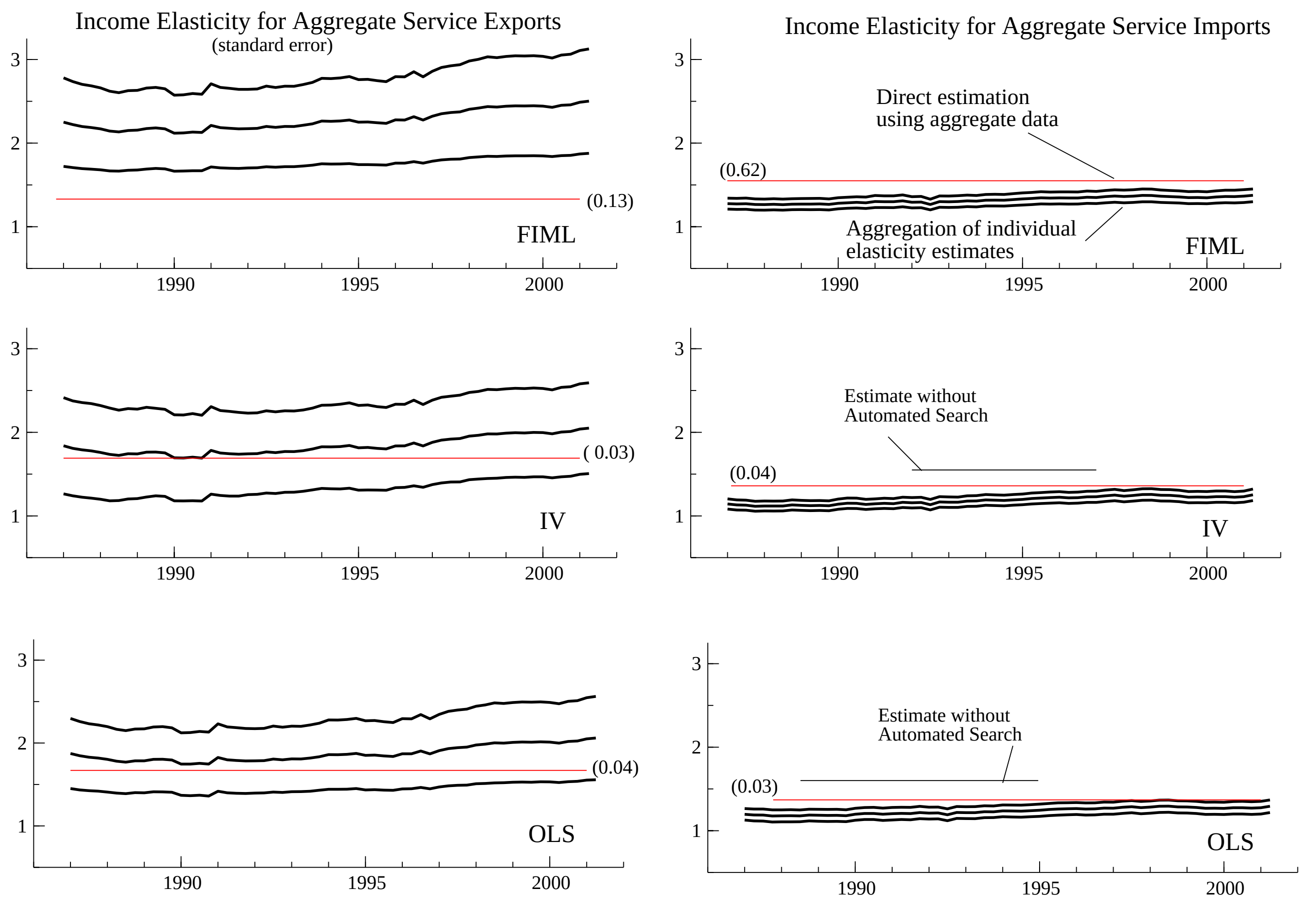


Figure 12



Income Elasticity for Aggregate Service Exports
(standard error)
(0.13)
FIML
IV
(0.03)
OLS
(0.04)
Income Elasticity for Aggregate Service Imports
Direct estimation
using aggregate data
(0.62)
Aggregation of individual
elasticity estimates
Estimate without
Automated Search
(0.04)
Estimate without
Automated Search
(0.03)
1990
1995
2000

Figure 13

Table 1: Income and Price Elasticities for Exports of Imports of Services – 1987-2001
Alternative Estimation Methods and Automated Specification Algorithms
Congruent Formulations*
(standard errors)

Category	Exports				Imports			
	Income	Price	Estimation Method	Search Algorithm	Income	Price	Estimation Method	Search Algorithm
Aggregate	1.33* (0.13)	-0.37 (0.20)	FIML	None	1.55* (0.62)	-0.92* (0.16)	FIML	None
	1.69* (0.03)	-0.27* (0.02)	IV	Liberal	1.36* (0.04)	-1.57* (0.07)	IV	Liberal
	1.67* (0.04)	-0.26* (0.02)	OLS	Liberal	1.37* (0.03)	-1.60* (0.05)	OLS	Conservative
Other Private	3.79* (0.65)	-1.52* (0.32)	FIML	None	1.73* (0.10)	-2.51* (0.19)	FIML	None
	3.20* (0.51)	-1.14* (0.26)	IV	Liberal	1.49* (0.06)	-2.10* (0.11)	IV	Conservative
	3.12* (0.52)	-1.08* (0.26)	OLS	Liberal	1.50* (0.08)	-2.11* (0.15)	OLS	Liberal
Fares	1.11* (0.21)	-1.43* (0.58)	FIML	None	2.11* (0.09)	-0.92* (0.20)	FIML	None
	0.10 (0.84)	-2.02* (1.12)	IV	None	2.47* (0.17)	-1.53* (0.34)	IV	Liberal
	0.59 (0.61)	0.01 (0.30)	OLS	Liberal	2.36* (0.13)	-1.37* (0.29)	OLS	Liberal
Transportation	0.95* (0.27)	-0.53* (0.36)	FIML	None	0.91* (0.07)	-0.14 (0.16)	FIML	None
	0.86* (0.86)	-0.09* (0.04)	IV	Liberal	0.36* (0.01)	0.00 --	IV	Liberal
	0.99* (0.10)	-0.17* (0.05)	OLS	Liberal	0.65* (0.10)	-0.53* (0.19)	OLS	Conservative
Travel	1.57* (0.17)	-0.79* (0.19)	FIML	None	1.04* (0.03)	-1.56* (0.10)	FIML	None
	1.32* (0.12)	-0.77* (0.15)	IV	Conservative	1.09* (0.05)	-1.43* (0.16)	IV	None
	1.30* (0.09)	-0.76* (0.12)	OLS	Conservative	1.08* (0.02)	-1.26* (0.04)	OLS	Liberal

*Statistically significant at the 5 percent level.
**Selection: Lowest SER among functional forms that satisfy congruence.

Table 2: Income Elasticities for Disaggregate Trade in Services
Gains from Automated Specification

Category	IV				OLS				Shares	
	Exports		Imports		Exports		Imports			
	Search	No Search	Search	No Search	Search	No Search	Search	No Search	Ex.	Im.
Other Private	3.20*	3.26*	1.49*	2.18	3.12*	3.23*	1.50*	2.26	47	32
Fares	0.10	0.10	2.47*	2.12*	0.60	0.40	2.36*	2.12	8	13
Transportation	0.86*	1.12*	0.36*	0.73	0.99*	0.92*	0.65*	0.73	12	22
Travel	1.32*	1.12*	1.09*	1.09*	1.30*	1.48*	1.08*	1.07*	33	33

Table A1: Income and Price Elasticities for Exports of Aggregate Services – 1987-2001
Alternative Estimation Methods and Automated Specification Algorithms

Lags	Method	Income	Own-Price	JB	AR	ARCH	SER-GUM(%)	SER-Spec (%)	Par-GUM	Par-Spec	Max Lag in Spec
8	OLS & No-search	0.99	-0.70	Y	Y	Y	1.50	1.50	28	28	8
	OLS & Lib. Search	1.67*	-0.26*	Y	Y	Y	1.50	1.32	28	7	6
	OLS & Con. Search	1.74*	-0.29*	Y	Y	Y	1.50	1.51	28	4	6
	IV & No-search	0.00e	-1.12*	y	Y	y	1.51	1.51	28	28	8
	IV & Lib. Search	1.69*	-0.27*	Y	Y	Y	1.51	1.37	28	5	6
	IV & Con. Search	1.74*	-0.29*	Y	Y	Y	1.51	1.50	28	4	6
6	OLS & No-search	1.29*	-0.50	Y	Y	Y	1.35	1.35	22	22	6
	OLS & Lib. Search	1.67*	-0.26*	Y	Y	Y	1.35	1.32	22	7	6
	OLS & Con. Search	1.69*	-0.27*	Y	Y	Y	1.35	1.38	22	5	6
	IV & No-search	3.01	-0.06	y	Y	Y	2.89	2.89	22	22	6
	IV & Lib. Search	0.00e	+0.61*	Y	Y	Y	2.89	2.44	22	5	6
	IV & Con. Search	0.00e	+0.59*	Y	Y	Y	2.89	2.46	22	4	1
4	OLS & No-search	1.67*	-0.26*	Y	Y	y	1.59	1.59	16	16	4
	OLS & Lib. Search	1.74*	-0.29*	Y	Y	Y	1.59	1.50	16	5	4
	OLS & Con. Search	1.76*	-0.30*	Y	Y	Y	1.59	1.53	16	4	4
	IV & No-search	0.20	-0.34	Y	Y	y	2.29	2.29	16	16	4
	IV & Lib. Search	1.76*	-0.30*	Y	Y	y	2.29	1.59	16	4	3
	IV & Con. Search	1.77*	-0.30*	Y	Y	Y	2.29	1.69	16	4	1

	FIML: Number of lags in the VAR			
	8	6	4	2
Income Elasticity	1.81*	3.14*	1.33*	1.67*
Own-Price Elasticity	-0.17	+0.56	0.37*	-0.23
Loading Coefficient	-0.20	+0.05	-0.188	-0.28*
No. Cointegation vectors	2	2	1	0
JB	Y	Y	Y	Y
AR	Y	Y	Y	Y
ARCH	Na	Y	Y	Y

*Statistically significant at the 5 percent level
JB: Jarque-Bera test for normality
AR: Test of Serial independence for the residuals
ARCH test of constant
SER-GUM: Standard error of the regression associated with the General Unrestricted Model
SER-Spec: Standard error of the regression associated with the Specific Model
Par-GUM: Number of parameters in the General Unrestricted Model
Par-Spec: Number of parameters estimated in the Specific Model
Max-Lag in Spec: Maximun lag-length in the Specific Model

Table A2: Income and Price Elasticities for Imports of Aggregate Services – 1987-2001
Alternative Estimation Methods and Automated Specification Algorithms

Lags	Method	Income	Own-Price	JB	AR	ARCH	SER-GUM(%)	SER-Spec (%)	Par-GUM	Par-Spec	Max Lag in Spec
8	OLS & No-search	1.72*	-0.15	Y	Y	Y	1.96	1.96	28	28	8
	OLS & Lib. Search	1.36*	-1.58*	Y	Y	Y	1.96	1.74	28	6	6
	OLS & Con. Search	1.37*	-1.60*	Y	Y	Y	1.96	1.75	28	5	3
	IV & No-search	2.92	+4.64	Y	N	Y	2.50	2.50	28	28	8
	IV & Lib. Search	1.78*	0.00e	Y	N	Y	2.50	1.90	28	6	6
	IV & Con. Search	0.00e	0.00e	Y	N	Y	2.50	2.29	28	3	1
6	OLS & No-search	1.49*	-0.99	Y	N	Y	1.83	1.83	22	22	6
	OLS & Lib. Search	1.40*	-1.65*	Y	N	Y	1.83	1.79	22	5	5
	OLS & Con. Search	1.40*	-1.65*	Y	Y	Y	1.83	1.79	22	5	5
	IV & No-search	2.18	+1.71	Y	N	Y	2.72	2.72	22	22	6
	IV & Lib. Search	1.78*	0.00e	Y	N	Y	2.72	1.90	22	6	6
	IV & Con. Search	1.78*	0.00e	Y	N	Y	2.72	1.90	22	6	6
4	OLS & No-search	1.47*	-1.10*	Y	Y	Y	1.75	1.75	16	16	4
	OLS & Lib. Search	1.37*	-1.60*	N	Y	Y	1.75	1.68	16	9	4
	OLS & Con. Search	1.37*	-1.60*	Y	Y	Y	1.75	1.75	16	5	3
	IV & No-search	1.32*	-1.62	Y	Y	Y	1.77	1.77	16	16	4
	IV & Lib. Search	1.36*	-1.57	Y	Y	Y	1.77	1.66	16	8	4
	IV & Con. Search	1.76*	0.00e	Y	Y	Y	1.77	1.84	16	6	3

	FIML: Number of lags in the VAR			
	8	6	4	2
Income Elasticity	3.14*	3.47*	2.07*	1.55*
Own-Price Elasticity	+5.25*	+6.96*	-1.23	-0.92*
Loading Coefficient	-0.22*	-0.13*	-0.35*	-0.27*
No. Cointegation vectors	0	0	1	2
JB	Y	Y	Y	Y
AR	Y	Y	Y	N
ARCH	Na	Y	Y	Y

*Statistically significant at the 5 percent level
JB: Jarque-Bera test of null hypothesis of normality in the residuals
AR: Test of null hypothesis of serial independence for the residuals
ARCH: Test of null hypothesis of constant variance of the residuals
SER-GUM: Standard error of the regression associated with the General Unrestricted Model
SER-Spec: Standard error of the regression associated with the Specific Model
Par-GUM: Number of parameters in the General Unrestricted Model
Par-Spec: Number of parameters estimated in the Specific Model
Max-Lag in Spec: Maximun lag-length in the Specific Model
Y: One cannot reject the associated null hypothesis
N: One cannot accept the associated null hypothesis
e: automated specification excludes this variable

Table A3: Income and Price Elasticities for Exports of Other Private Services – 1987-2001
Alternative Estimation Methods and Automated Specification Algorithms

Lags	Method	Income	Own-Price	JB	AR	ARCH	SER-GUM(%)	SER-Spec (%)	Par-GUM	Par-Spec	Max Lag in Spec
8	OLS & No-search	3.18*	+0.49	Y	Y	Y	1.76	1.76	27	27	8
	OLS & Lib. Search	3.28*	+0.47*	Y	Y	Y	1.76	1.54	27	10	6
	OLS & Con. Search	3.25*	+0.46*	Y	Y	Y	1.76	1.78	27	5	5
	IV & No-search	3.60	-1.12	Y	Y	Y	2.37	2.37	27	27	8
	IV & Lib. Search	4.48	-1.73	Y	Y	Y	2.37	1.87	27	9	7
	IV & Con. Search	0.00e	0.00e	Y	Y	Y	2.37	1.98	27	1	1
6	OLS & No-search	3.23*	+0.48	Y	Y	Y	1.64	1.64	21	21	6
	OLS & Lib. Search	3.12*	-1.08*	Y	Y	Y	1.64	1.47	21	11	6
	OLS & Con. Search	8.50	0.00e	Y	Y	Y	1.64	1.69	21	6	5
	IV & No-search	3.26*	+0.35	Y	Y	Y	1.86	1.86	21	21	6
	IV & Lib. Search	3.20*	-1.14*	Y	Y	Y	1.86	1.53	21	11	6
	IV & Con. Search	6.03	0.00e	Y	Y	Y	1.86	1.69	21	6	5
4	OLS & No-search	3.23*	+0.54*	Y	Y	Y	1.84	1.84	15	15	4
	OLS & Lib. Search	3.25*	0.48*	Y	Y	Y	1.84	1.74	15	7	4
	OLS & Con. Search	0.00e	0.00e	Y	Y	Y	1.84	1.98	15	1	1
	IV & No-search	3.27*	+0.49*	Y	Y	Y	2.32	2.32	15	15	4
	IV & Lib. Search	3.22*	+0.48*	Y	Y	Y	2.32	1.93	15	5	1
	IV & Con. Search	0.00e	0.00e	Y	Y	Y	2.32	1.98	15	1	1

	FIML: lags in the VAR		
	8	6	4
Income Elasticity	4.09*	3.79*	2.57*
Own-Price Elasticity	-1.72	-1.52*	-0.75*
Loading Coefficient	0.01	0.01	-0.03*
No. Cointegation vectors	2	1	0
JB	Y	Y	Y
AR	Y	Y	Y
ARCH	Na	Y	Y

*Statistically significant at the 5 percent level
JB: Jarque-Bera test of null hypothesis of normality in the residuals
AR: Test of null hypothesis of serial independence for the residuals
ARCH: Test of null hypothesis of constant variance of the residuals
SER-GUM: Standard error of the regression associated with the General Unrestricted Model
SER-Spec: Standard error of the regression associated with the Specific Model
Par-GUM: Number of parameters in the General Unrestricted Model
Par-Spec: Number of parameters estimated in the Specific Model
Max-Lag in Spec: Maximun lag-length in the Specific Model
Y: One cannot reject the associated null hypothesis
N: One cannot accept the associated null hypothesis
e: automated specification excludes this variable

Table A4: Income and Price Elasticities for Exports of Other Private Services – 1987-2001
Alternative Estimation Methods and Automated Specification Algorithms

Lags	Method	Income	Own-Price	JB	AR	ARCH	SER-GUM(%)	SER-Spec (%)	Par-GUM	Par-Spec	Max Lag in Spec
8	OLS & No-search	5.00*	-0.97	Y	Y	Y	4.89	4.89	28	28	8
	OLS & Lib. Search	0.00e	-3.94*	Y	Y	Y	4.89	4.26	28	7	8
	OLS & Con. Search	0.00e	-3.94*	N	N	Y	4.89	4.26	28	7	8
	IV & No-search	4.63*	+2.01	Y	Y	Y	5.15	5.15	28	28	8
	IV & Lib. Search	1.39*	-1.91*	Y	Y	Y	5.15	4.10	28	7	8
	IV & Con. Search	1.39*	-1.91*	Y	Y	Y	5.15	4.10	28	7	8
6	OLS & No-search	2.26	-1.31	Y	Y	Y	4.79	4.79	22	22	6
	OLS & Lib. Search	1.54*	-1.09*	Y	N	Y	4.79	4.10	22	6	3
	OLS & Con. Search	3.10*	-0.74*	N	Y	Y	4.79	4.32	22	4	2
	IV & No-search	2.97	-0.46	Y	Y	Y	4.86	4.86	22	22	6
	IV & Lib. Search	1.50*	-2.11	Y	Y	Y	4.86	4.30	22	7	2
	IV & Con. Search	3.10	0e	Y	Y	Y	4.86	4.32	22	4	2
4	OLS & No-search	2.86*	-0.47	Y	Y	Y	4.44	4.44	16	16	4
	OLS & Lib. Search	0.00e	-4.12*	Y	N	Y	4.44	4.22	16	7	4
	OLS & Con. Search	0.00e	-4.12*	Y	N	Y	4.44	4.22	16	7	4
	IV & No-search	2.18	-1.06	Y	Y	Y	5.13	5.13	16	16	4
	IV & Lib. Search	1.52*	-2.14*	Y	Y	Y	5.13	4.07	16	7	4
	IV & Con. Search	1.49*	-2.10*	Y	Y	Y	5.13	4.30	16	4	3

	FIML: Number of lags in the VAR			
	8	6	4	3
Income Elasticity	1.09	0.66	1.73*	1.70*
Own-Price Elasticity	-1.56	-0.74	-2.51*	-2.45*
Loading Coefficient	0.03	0.03	-0.18	-0.20*
No. Cointegation vectors	0	2	2	1
JB	N	N	N	N
AR	Y	Y	Y	Y
ARCH	Na	Y	Y	Y

*Statistically significant at the 5 percent level
JB: Jarque-Bera test of null hypothesis of normality in the residuals
AR: Test of null hypothesis of serial independence for the residuals
ARCH: Test of null hypothesis of constant variance of the residuals
SER-GUM: Standard error of the regression associated with the General Unrestricted Model
SER-Spec: Standard error of the regression associated with the Specific Model
Par-GUM: Number of parameters in the General Unrestricted Model
Par-Spec: Number of parameters estimated in the Specific Model
Max-Lag in Spec: Maximun lag-length in the Specific Model
Y: One cannot reject the associated null hypothesis
N: One cannot accept the associated null hypothesis
e: automated specification excludes this variable

Table A5: Income and Price Elasticities for Exports of Fares – 1987-2001
Alternative Estimation Methods and Automated Specification Algorithms

lags	Method	Income	Own-Price	JB	AR	ARCH	SER-GUM(%)	SER-Spec (%)	Par-GUM	Par-Spec	Max Lag in Spec
8	OLS & No-search	0.40	-1.07	Y	Y	Y	5.31	5.31	28	28	8
	OLS & Lib. Search	0.59	0.01	Y	Y	Y	5.31	4.47	28	9	8
	OLS & Con. Search	0.00e	0.00e	Y	Y	Y	5.31	5.07	28	3	1
	IV & No-search	0.10	-2.02*	Y	Y	Y	7.85	7.85	28	28	8
	IV & Lib. Search	0.00e	0.32*	Y	Y	Y	7.85	7.10	28	3	6
	IV & Con. Search	0.00e	0.32*	Y	Y	Y	7.85	5.10	28	3	6
6	OLS & No-search	-0.68	-2.39	Y	Y	Y	4.98	4.98	22	22	6
	OLS & Lib. Search	-1.94	1.2	Y	Y	N	4.98	4.81	22	7	6
	OLS & Con. Search	0.00e	+0.32*	Y	Y	Y	4.98	5.14	22	3	5
	IV & No-search	-0.51	-2.45	N	Y	Y	6.10	6.10	22	22	6
	IV & Lib. Search	0.00e	0.00e	N	Y	Y	6.10	4.95	22	4	2
	IV & Con. Search	0.00e	0.00e	N	Y	Y	6.10	5.14	22	3	1
4	OLS & No-search	-0.04	-1.18	Y	Y	Y	5.12	5.12	16	16	4
	OLS & Lib. Search	0.00e	0.00e	Y	Y	Y	5.12	4.95	16	4	2
	OLS & Con. Search	0.00e	+0.32*	Y	Y	Y	5.12	5.14	16	3	1
	IV & No-search	-0.33	-1.61	N	Y	Y	6.16	6.16	16	16	4
	IV & Lib. Search	0.00e	0.00e	N	Y	Y	6.16	4.95	16	4	2
	IV & Con. Search	0.00e	0.00e	N	Y	Y	6.16	5.07	16	3	1

	FIML: Number of lags in the VAR			
	8	6	4	2
Income Elasticity	0.51	1.11*	2.76	1.88
Own-Price Elasticity	-2.10*	-1.43*	-2.03*	-2.29*
Loading Coefficient	-0.09	0.01	0.10	0.04
No. Cointegation vectors	1	1	0	0
JB	Y	Y	N	N
AR	Y	Y	Y	Y
ARCH	Na	Y	Y	Y

*Statistically significant at the 5 percent level
JB: Jarque-Bera test of null hypothesis of normality in the residuals
AR: Test of null hypothesis of serial independence for the residuals
ARCH: Test of null hypothesis of constant variance of the residuals
SER-GUM: Standard error of the regression associated with the General Unrestricted Model
SER-Spec: Standard error of the regression associated with the Specific Model
Par-GUM: Number of parameters in the General Unrestricted Model
Par-Spec: Number of parameters estimated in the Specific Model
Max-Lag in Spec: Maximun lag-length in the Specific Model
Y: One cannot reject the associated null hypothesis
N: One cannot accept the associated null hypothesis
e: automated specification excludes this variable

Table A6: Income and Price Elasticities for Imports of Fares – 1987-2001
Alternative Estimation Methods and Automated Specification Algorithms

Lags	Method	Income	Own-Price	JB	AR	ARCH	SER-GUM(%)	SER-Spec (%)	Par-GUM	Par-Spec	Max Lag in Spec
8	OLS & No-search	2.12*	-0.62*	Y	Y	Y	3.46	3.46	29	29	8
	OLS & Lib. Search	2.36*	-1.37*	Y	Y	Y	3.46	3.00	29	9	7
	OLS & Con. Search	0.00e	0.05	Y	Y	Y	3.46	3.30	29	7	7
	IV & No-search	2.12*	-0.62	Y	Y	Y	3.46	3.46	29	29	8
	IV & Lib. Search	2.47*	-1.53*	Y	Y	Y	3.46	2.99	29	10	7
	IV & Con. Search	4.59*	-8.22*	Y	Y	Y	3.46	3.53	29	5	5
6	OLS & No-search	2.23*	-1.06*	Y	Y	Y	3.41	3.41	23	23	6
	OLS & Lib. Search	2.36*	-1.28*	Y	Y	Y	3.41	3.18	23	8	5
	OLS & Con. Search	2.08*	-1.20*	Y	Y	Y	3.41	3.49	23	6	6
	IV & No-search	2.23*	-1.06*	Y	Y	Y	3.41	3.41	23	23	6
	IV & Lib. Search	2.29*	-1.22*	Y	Y	Y	3.41	3.10	23	10	6
	IV & Con. Search	2.33*	-1.22*	Y	Y	Y	3.41	3.94	23	4	1
4	OLS & No-search	2.37*	-1.43*	Y	Y	Y	3.39	3.39	17	17	4
	OLS & Lib. Search	2.38*	-1.38*	Y	Y	Y	3.39	3.19	17	7	4
	OLS & Con. Search	2.38*	-1.38*	Y	Y	Y	3.39	3.19	17	7	4
	IV & No-search	2.37*	-1.43*	Y	Y	N	3.39	3.39	17	17	4
	IV & Lib. Search	2.46*	-1.49*	Y	Y	Y	3.39	3.21	17	8	4
	IV & Con. Search	2.45*	-1.49*	Y	Y	Y	3.39	3.21	17	8	4

	FIML: Number of lags in the VAR			
	8	6	4	2
Income Elasticity	0.93*	2.11*	2.93*	-0.12
Own-Price Elasticity	+1.10	-0.92*	-2.45*	+3.31*
Loading Coefficient	0.09	-0.28*	-0.28*	0.02
No. Cointegation vectors	2	1	2	2
JB	Y	Y	Y	Y
AR	Y	N	Y	Y
ARCH	Na	Y	Y	Y

*Statistically significant at the 5 percent level
JB: Jarque-Bera test of null hypothesis of normality in the residuals
AR: Test of null hypothesis of serial independence for the residuals
ARCH: Test of null hypothesis of constant variance of the residuals
SER-GUM: Standard error of the regression associated with the General Unrestricted Model
SER-Spec: Standard error of the regression associated with the Specific Model
Par-GUM: Number of parameters in the General Unrestricted Model
Par-Spec: Number of parameters estimated in the Specific Model
Max-Lag in Spec: Maximun lag-length in the Specific Model
Y: One cannot reject the associated null hypothesis
N: One cannot accept the associated null hypothesis
e: automated specification excludes this variable

Table A7: Income and Price Elasticities for Exports of Transportation – 1987-2001
Alternative Estimation Methods and Automated Specification Algorithms

Lags	Method	Income	Own-Price	JB	AR	ARCH	SER-GUM(%)	SER-Spec (%)	Par-GUM	Par-Spec	Max Lag in Spec
8	OLS & No-search	0.92*	-0.12	Y	Y	Y	2.24	2.24	28	28	8
	OLS & Lib. Search	0.99*	-0.17*	Y	Y	Y	2.24	2.08	28	11	8
	OLS & Con. Search	0.76*	-0.04	Y	Y	Y	2.24	2.19	28	8	7
	IV & No-search	1.12*	-0.06	Y	Y	Y	2.78	2.78	28	28	8
	IV & Lib. Search	0.86*	-0.09*	Y	Y	Y	2.78	2.33	28	8	8
	IV & Con. Search	0.69	0.00e	Y	Y	Y	2.78	2.84	28	3	2
6	OLS & No-search	0.95*	-0.16	Y	Y	Y	2.31	2.31	22	22	6
	OLS & Lib. Search	0.95*	-0.14	Y	Y	Y	2.31	2.21	22	10	6
	OLS & Con. Search	0.89*	-0.11	Y	Y	Y	2.31	2.41	22	7	4
	IV & No-search	0.96*	-0.18	Y	Y	Y	2.32	2.32	22	22	6
	IV & Lib. Search	0.69*	0.00e	Y	Y	Y	2.32	2.63	22	5	4
	IV & Con. Search	0.69*	0.00e	Y	Y	Y	2.32	2.63	22	5	4
4	OLS & No-search	0.69*	-0.57	Y	Y	Y	2.44	2.44	16	16	4
	OLS & Lib. Search	0.89*	-0.11	Y	Y	Y	2.44	2.41	16	7	4
	OLS & Con. Search	0.89*	-0.11*	Y	Y	Y	2.44	2.41	16	7	4
	IV & No-search	0.88	-0.68	Y	Y	Y	2.62	2.62	16	16	4
	IV & Lib. Search	0.69*	0.00e	Y	Y	Y	2.62	2.62	16	5	4
	IV & Con. Search	0.69*	0.00e	Y	Y	Y	2.62	2.79	16	3	2

	FIML: Number of lags in the VAR			
	8	6	4	2
Income Elasticity	1.05*	1.08*	0.95*	0.85*
Own-Price Elasticity	-0.10	-0.28	-0.53*	-0.04
Loading Coefficient	0.04	-0.07	-0.09*	-0.16*
No. Cointegation vectors	1	1	1	1
JB	Y	Y	Y	Y
AR	Y	Y	Y	Y
ARCH	Na	Y	Y	Y

*Statistically significant at the 5 percent level
JB: Jarque-Bera test of null hypothesis of normality in the residuals
AR: Test of null hypothesis of serial independence for the residuals
ARCH: Test of null hypothesis of constant variance of the residuals
SER-GUM: Standard error of the regression associated with the General Unrestricted Model
SER-Spec: Standard error of the regression associated with the Specific Model
Par-GUM: Number of parameters in the General Unrestricted Model
Par-Spec: Number of parameters estimated in the Specific Model
Max-Lag in Spec: Maximun lag-length in the Specific Model
Y: One cannot reject the associated null hypothesis
N: One cannot accept the associated null hypothesis
e: automated specification excludes this variable

Table A8: Income and Price Elasticities for Imports of Transportation– 1987-2001
Alternative Estimation Methods and Automated Specification Algorithms

Lags	Method	Income	Own-Price	JB	AR	ARCH	SER-GUM(%)	SER-Spec (%)	Par-GUM	Par-Spec	Max Lag in Spec
8	OLS & No-search	0.84*	+0.50*	Y	Y	Y	2.74	2.74	29	29	8
	OLS & Lib. Search	0.75*	+0.39*	Y	Y	Y	2.74	2.52	29	6	6
	OLS & Con. Search	0.87*	0.00e	Y	Y	Y	2.74	2.68	29	3	5
	IV & No-search	0.73	0.80	Y	Y	Y	3.04	3.04	29	29	8
	IV & Lib. Search	0.36*	0.00e	Y	Y	Y	3.04	2.55	29	3	8
	IV & Con. Search	0.36*	0.00e	Y	Y	Y	3.04	2.66	29	3	1
6	OLS & No-search	0.54*	-0.01	Y	Y	Y	2.62	2.62	23	23	6
	OLS & Lib. Search	0.50*	-0.25*	Y	Y	Y	2.62	2.42	23	7	6
	OLS & Con. Search	0.63*	-0.53*	Y	Y	Y	2.62	2.68	23	3	5
	IV & No-search	0.80*	0.16	Y	Y	Y	4.48	4.48	23	23	6
	IV & Lib. Search	0.00e	0.00e	Y	Y	Y	4.48	2.88	23	1	1
	IV & Con. Search	0.00e	0.00e	Y	Y	Y	4.48	2.88	23	1	1
4	OLS & No-search	0.60*	0.42	Y	Y	Y	2.74	2.74	17	17	4
	OLS & Lib. Search	0.78*	0.31*	Y	Y	Y	2.74	2.53	17	5	1
	OLS & Con. Search	0.82*	0.00e	Y	Y	Y	2.74	2.62	17	3	1
	IV & No-search	0.84*	0.32	Y	Y	Y	3.98	3.98	17	17	4
	IV & Lib. Search	0.83*	0.00e	Y	Y	Y	3.98	2.65	17	3	2
	IV & Con. Search	0.83	0.00e	Y	Y	Y	3.98	2.65	17	3	2

	FIML: Number of lags in the VAR			
	8	6	4	2
Income Elasticity	-0.37	0.87*	0.91*	0.91*
Own-Price Elasticity	+2.45	+0.20	+0.30	-0.14
Loading Coefficient	-0.06*	-0.32	-0.19	-0.10
No. Cointegation vectors	2	0	0	1
JB	Y	Y	Y	N
AR	N	Y	Y	Y
ARCH	Na	Y	Y	Y

*Statistically significant at the 5 percent level
JB: Jarque-Bera test of null hypothesis of normality in the residuals
AR: Test of null hypothesis of serial independence for the residuals
ARCH: Test of null hypothesis of constant variance of the residuals
SER-GUM: Standard error of the regression associated with the General Unrestricted Model
SER-Spec: Standard error of the regression associated with the Specific Model
Par-GUM: Number of parameters in the General Unrestricted Model
Par-Spec: Number of parameters estimated in the Specific Model
Max-Lag in Spec: Maximun lag-length in the Specific Model
Y: One cannot reject the associated null hypothesis
N: One cannot accept the associated null hypothesis
e: automated specification excludes this variable

Table A9: Income and Price Elasticities for Exports of Travel – 1987-2001
Alternative Estimation Methods and Automated Specification Algorithms

Lags	Method	Income	Own-Price	JB	AR	ARCH	SER-GUM(%)	SER-Spec (%)	Par-GUM	Par-Spec	Max Lag in Spec
8	OLS & No-search	1.48*	-0.68*	Y	Y	Y	4.17	4.17	27	27	8
	OLS & Lib. Search	1.30*	-0.76*	Y	Y	Y	4.17	3.48	27	4	8
	OLS & Con. Search	1.30*	-0.76*	Y	Y	Y	4.17	3.48	27	4	8
	IV & No-search	1.53*	-0.67*	Y	Y	Y	4.19	4.19	27	27	8
	IV & Lib. Search	1.45*	-0.26*	Y	Y	Y	4.19	3.58	27	5	8
	IV & Con. Search	1.44*	-0.26*	Y	Y	Y	4.19	3.58	27	5	8
6	OLS & No-search	1.34*	-0.78*	Y	Y	Y	4.00	4.00	21	21	6
	OLS & Lib. Search	1.27*	-0.85*	Y	Y	Y	4.00	3.66	21	4	4
	OLS & Con. Search	1.47*	-0.65*	Y	Y	Y	4.00	3.87	21	4	2
	IV & No-search	0.22	-0.73*	Y	Y	Y	5.47	5.47	21	21	6
	IV & Lib. Search	0.00e	+0.46*	Y	Y	Y	5.47	4.85	21	3	2
	IV & Con. Search	0.00e	0.00e	Y	Y	Y	5.47	4.35	21	2	2
4	OLS & No-search	1.41*	-0.83*	Y	Y	Y	3.85	3.85	15	15	4
	OLS & Lib. Search	1.27*	-0.85*	Y	Y	Y	3.85	3.66	15	4	4
	OLS & Con. Search	1.32*	-0.77*	Y	Y	Y	3.85	3.76	15	4	3
	IV & No-search	1.12*	-0.81*	Y	Y	Y	4.35	4.35	15	15	4
	IV & Lib. Search	1.28*	-0.78*	Y	Y	Y	4.35	3.65	15	5	3
	IV & Con. Search	1.32*	-0.77*	Y	Y	Y	4.35	3.76	15	4	3

	FIML: Number of lags in the VAR			
	8	6	4	3
Income Elasticity	1.30*	1.57*	1.20*	1.04*
Own-Price Elasticity	-0.77*	-0.79*	-0.96*	-0.96*
Loading Coefficient	-0.32*	-0.20*	-0.35*	-0.26*
No. Cointegation vectors	2	1	0	1
JB	Y	Y	Y	Y
AR	Y	Y	Y	Y
ARCH	Na	Y	Y	Y

*Statistically significant at the 5 percent level
JB: Jarque-Bera test of null hypothesis of normality in the residuals
AR: Test of null hypothesis of serial independence for the residuals
ARCH: Test of null hypothesis of constant variance of the residuals
SER-GUM: Standard error of the regression associated with the General Unrestricted Model
SER-Spec: Standard error of the regression associated with the Specific Model
Par-GUM: Number of parameters in the General Unrestricted Model
Par-Spec: Number of parameters estimated in the Specific Model
Max-Lag in Spec: Maximun lag-length in the Specific Model
Y: One cannot reject the associated null hypothesis
N: One cannot accept the associated null hypothesis
e: automated specification excludes this variable

Table A10: Income and Price Elasticities for Imports of Travel – 1987-2001
Alternative Estimation Methods and Automated Specification Algorithms

Lags	Method	Income	Own-Price	JB	AR	ARCH	SER-GUM(%)	SER-Spec (%)	Par-GUM	Par-Spec	Max Lag in Spec
8	OLS & No-search	1.07*	-1.43*	Y	Y	Y	2.29	2.29	27	27	8
	OLS & Lib. Search	1.08*	-1.26*	Y	Y	Y	2.29	2.13	27	7	7
	OLS & Con. Search	1.08*	-1.26*	Y	Y	Y	2.29	2.22	27	5	7
	IV & No-search	1.06*	-1.48*	Y	Y	Y	2.35	2.35	27	27	8
	IV & Lib. Search	1.09*	-1.29*	Y	Y	Y	2.35	2.02	27	11	8
	IV & Con. Search	1.08*	-1.26*	Y	Y	Y	2.35	2.23	27	5	7
6	OLS & No-search	1.07*	-1.40*	Y	Y	Y	2.24	2.24	21	21	6
	OLS & Lib. Search	1.10*	-1.29*	Y	Y	Y	2.24	2.16	21	7	6
	OLS & Con. Search	1.09*	-1.28*	Y	Y	Y	2.24	2.35	21	4	4
	IV & No-search	1.08*	-1.40*	Y	Y	Y	2.28	2.28	21	21	6
	IV & Lib. Search	1.08*	-1.26*	Y	Y	Y	2.28	2.13	21	8	6
	IV & Con. Search	1.09*	-1.28*	Y	Y	Y	2.28	2.35	21	4	4
4	OLS & No-search	1.08*	-1.47*	Y	Y	Y	2.41	2.41	15	15	4
	OLS & Lib. Search	1.10*	-1.31*	Y	Y	Y	2.41	2.30	15	5	4
	OLS & Con. Search	1.09*	-1.28*	Y	Y	Y	2.41	2.35	15	4	4
	IV & No-search	1.09*	-1.43*	Y	Y	Y	2.45	2.45	15	15	4
	IV & Lib. Search	1.11*	-1.32*	Y	Y	Y	2.45	2.28	15	5	4
	IV & Con. Search	1.09*	-1.28*	Y	Y	Y	2.45	2.35	15	4	4

	FIML: Number of lags in the VAR			
	8	6	4	3
Income Elasticity	1.08*	1.05*	1.04*	1.07*
Own-Price Elasticity	-1.63*	-1.45*	-1.56*	-1.43*
Loading Coefficient	-0.85*	-1.19*	-0.82*	-0.89*
No. Cointegation vectors	0	1	1	1
JB	Y	Y	Y	Y
AR	Y	Y	Y	Y
ARCH	Na	Y	Y	Y

*Statistically significant at the 5 percent level
JB: Jarque-Bera test of null hypothesis of normality in the residuals
AR: Test of null hypothesis of serial independence for the residuals
ARCH: Test of null hypothesis of constant variance of the residuals
SER-GUM: Standard error of the regression associated with the General Unrestricted Model
SER-Spec: Standard error of the regression associated with the Specific Model
Par-GUM: Number of parameters in the General Unrestricted Model
Par-Spec: Number of parameters estimated in the Specific Model
Max-Lag in Spec: Maximun lag-length in the Specific Model
Y: One cannot reject the associated null hypothesis
N: One cannot accept the associated null hypothesis