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CHAPTER 5

EMPIRICAL DETERMINANTS OF SOUTH AFRICA-US INTRA-INDUSTRY TRADE IN SERVICES

We can see the past but not influence it; we can influence the future but not see it.

Stewart Brand (in Toastmasters International, 2002)

5.1 INTRODUCTION

This chapter builds on Chapter 2 and focuses on the empirical determinants of South Africa-US IIT in services. Empirical work on the measurement of IIT began in the 1960s with the work of Verdoon (1960), Balassa (1966) and Grubel and Lloyd (1975). These empirical researches galvanised trade economists to come up with various theoretical models of IIT extensively discussed in Chapter 2.

However, most theoretical and empirical investigations of these models of IIT have been confined to trade in goods. The anti-services bias of theoretical and empirical literature is succinctly articulated by Lee and Lloyd (2002:159) who point out that "…. the only discussion of intra-industry trade in services, to our knowledge, are those of the transportation services by Kierzkowski (1989) and the international telephone industry by Tang (1999)…"

The modelling process in this chapter is driven by two objectives. The first objective is to estimate an IIT model that adequately allows for differences in behaviour over service sectors as well as any differences in behaviour over time for a given service. Indeed, Gray (1988) argues for a model that allows for heterogeneity in behaviour when dealing

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with the phenomenon of IIT. The second objective is to use the most efficient estimation procedure given the short sample period. In view of the structural break owing to sanctions on South Africa before 1992, the analysis is done for the period 1994-2002[18].

The rest of the chapter is organised as follows. Under the backdrop of Chapter 2, Sections 5.2 and 5.3 survey theoretical and empirical literature relating to the determinants of IIT. Section 5.4 presents the specification of a dynamic logit model of South Africa-US IIT in unaffiliated services containing "country-specific", "industry-specific" factors and Hoekman openness indices constructed in Chapter 4. Sections 5.5 and 5.6 highlight data issues and estimation methodology. Section 5.7 describes statistical inference using first-order asymptotic theory (classical approach). Statistical inference using bootstrap techniques is explained in Section 5.8. Section 5.9 presents panel data unit root tests. Section 5.10 presents results of diagnostic tests of the residuals from the regression equation. Specifically, these entail tests of influential observations and heteroscedasticity. Sections 5.11 and 5.12 present the estimation and interpretation of the results. Main insights and concluding remarks are highlighted in Section 5.14.

5.2 THEORETICAL LITERATURE ON THE DETERMINANTS OF IIT

There is a great diversity of models in homogenous, horizontally and vertically differentiated IIT (HIIT and VIIT) extensively discussed in Chapter 2. The determinants and predictions of some these models are different and in some cases it is quite difficult to discriminate between them (Andresen, 2003). Despite these inherent problems, many empirical studies of IIT have tried to identify those features that are common to all, or most of these models. However, identification of these features is plagued with lack of appropriate data resulting to measurement errors since proxy variables are used in most

[18] This is an attempt to specify a regime-invariant model that avoids the Lucas (1976) policy critique. The lifting of sanctions in 1991, the new political dispensation in 1994, the readmission of South Africa in the World Trade Organisation (especially the participation in the General Agreement on Trade in Services in 1995) and general economic liberalization in the 1990s altered the "deep" structural parameters that characterize the fundamental behaviour of producers and consumers of services in South Africa.

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cases. Greenaway and Milner (1989) broadly classify determinants of IIT as "country-specific" and "industry-specific".

5.2.1 Country-specific determinants

The country-specific determinants are divided into five broad categories: economic development, market size, geographic proximity, economic integration and barriers to trade.

5.2.1.1 Economic distance/development

According to economic geography and "new economic geography" models launched by Krugman (1991) and Neary (2001) respectively, high levels of economic development are conducive to IIT because highly developed economies have the capacity to develop, produce and demand differentiated products.

There are two sides to this proposition; supply and demand. On the supply side, the extent of IIT in services is positively related to South Africa's per capita income. This proposition is consistent with models of IIT in goods, which can be extended to services of cross-border type (Lee and Lloyd, 2002:168).

Applying Falvey (1981) model to services, the higher-quality varieties of differentiated services are produced using relatively capital-intensive techniques. Similarly, adapting the Helpman and Krugman (1985) model to services, a differentiated service is assumed to be capital-intensive. The US, which is a higher-income country, is capital-abundant relative to South Africa and hence she specialises in the production of horizontally and vertically differentiated services.

On the demand side, the extent of IIT in services is positively correlated with South Africa's per capita income, through a more diversified pattern of demand for services. Linder's (1961) overlapping demand hypothesis, Drèze (1960), Helpman (1981), Balassa and Bauwens (1987) propose that the difference in per capita income represents a difference in the demand structure.

At the extreme, IIT will be highest when the two trading countries are identical in terms of economic development. The general expectation is that there is a negative relationship between IIT and the inequality of the levels of economic development of two countries. The most common measure of the inequality is the absolute value difference between GDP per capita of the two countries. This measure is affected by size bias. This can be seen when GDP for South Africa (country with small size) and the US (country with large size) are compared. However, Balassa (1986) formulated the following alternative index of relative inequality, which is robust to size bias;

$$ID = 1 + \frac{w\ln(w) + (1-w)\ln(1-w)}{\ln(2)}, ID \in (0,1) \tag{5.1}$$

Where;

ID=Relative measure which takes a value 0 to 1

$$w = \frac{(South \quad Africa \quad characteristic)}{(US \quad characteristic + South \quad Africa \quad characteristic)}$$

This index exhibits a number of characteristics. Firstly, as w approaches ½, ID approaches 0 while as w tends towards either 1 or 0, ID will take the value close to 1. Secondly, this variable is symmetrical with respect to country characteristics; it is not affected by a change in the unit of measurement and is a convex function of w.

5.2.1.2 Market size

Market size is positively related to the intensity of IIT. Both models of "love of variety"(Krugman, 1979) or "the ideal-variety" (Lancaster, 1980), discussed in Chapter 2, suggest that larger markets have the potential to allow for greater differentiation in products/services. Larger markets also have the potential for exploitation of economies

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of scale. Most studies use GDP as a proxy for market size. The Balassa (1986) inequality in Equation 5.1 is modified to capture relative market size differentials.

5.2.1.3 Geographical proximity (space)

This is based on the gravity model of trade and there are three determinants. Firstly, two geographically close countries have lower transport costs and therefore have greater IIT intensity. Secondly, two geographically close countries would have similar culture and tastes, which increases the potential for IIT (demand similarity hypothesis). Thirdly, countries, which are close geographically, are likely to have similar resource base and therefore high specialisation within similar industries. The globalisation process and the creation of a "global village" have reduced the importance of geographical proximity.

Most studies of IIT use dummy variables, which takes a value of 1 if the two countries share a common border or a measure of the distance between the capital cities of the two countries (kilometres or miles) to capture geographic proximity. The expectation is that shorter distances and a common border increase the intensity of IIT. The problem with this approach is that it is only useful for cross-country studies (where the analysis tries to identify contemporaneous cross-country variations). In bilateral studies, these variables for each country would be constant over time.

5.2.1.4 Economic integration

Economic integration is deemed to increase the potential for IIT. Any form of integration (e.g., customs union or monetary union) lowers or eliminates barriers to trade thus lowering transaction costs of the trade. Moreover, economic integration, if for a long time, can be a proxy for culturally similar countries, which increases IIT. In most studies, the economic integration variable is represented by a dummy variable taking on the value of 1 if two countries are in an economic integration of any sort. For the case of South Africa and the US the economic integration variable would start playing some role once the SACU-US FTA is in place.

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5.2.1.5 Barriers to trade

Falvey (1981) demonstrates that countries with lower trade barriers have higher levels of IIT. Balassa (1986), in a bid to capture non-tariff barriers, calculated trade orientation variable that measures deviations from a hypothetical level of per capita exports. Countries that have higher than the hypothetical value have low non-tariff barriers to trade, while countries with lower than hypothetical values have high non-tariff barriers to trade.

Although there have been many trade barriers and restrictive national regulations, a new era of free trade in services following the successful conclusion of the Uruguay Round in 1994, has seen growth in the importance of service liberalization and deregulation in the whole world.

5.2.1.6 Exchange rate

Although IIT models do not include nominal exchange rate, there are attempts in general trade literature to link exchange rate to international trade. These models are dealt with in Bowen *et al.* (1998:537-561). Exporting firms respond incompletely to exchange rate movements by adjusting their export prices and mark-up over marginal costs. Consequently, the relationship between exchange rate and IIT is an empirical question.

5.2.2 Industry-specific determinants

These determinants cover the categories of product differentiation, economies of scale, market structure, product life cycle and the role of multinational corporations.

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5.2.2.1 Product/service differentiation

One measure for product differentiation within an industry is the number of product/service categories within an industry. Andresen (2003) argues that this counting of categories may not capture the product differentiation appropriately. Indeed, there are other indices that capture product differentiation.

The first and the commonly used measure is an index formulated by Hufbauer (1970);

$$H = \frac{\sigma_{ij}}{M_{ij}} \tag{5.2}$$

Where σ_{ij} represents the standard deviation of export unit values for shipments of good *i* to country *j* and M_{ij} is the unweighted mean of those unit values. An increase in the variance of the export unit values reflects an increase in product differentiation.

The second index by Fontagńe and Freudenberg (1997), which is also used to differentiate between horizontal (variety) and vertical (quality) differentiation, utilises industry-weighted average of unit value ratios:

$$Differentiation = \sum_{i=1}^{n} \left[\frac{value_{ij}}{value_j} \left(\frac{Max(UV_{ij})}{Min(UV_{ij})} \right) \right] \tag{5.3}$$

Where $value_{ij} \equiv$ value of trade for good *i* in industry *j*, $value_j \equiv$ value of trade in industry *j*, $Max(UV_{ij}) \equiv$ the higher unit value (export or import) of good *i* in industry j, $Min(UV_{ij}) \equiv$ the lower unit value (export or import) of good *i* in industry j and ranges from 1 to infinity. This measures the dispersion of unit value ratios for an industry.

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For horizontal differentiation, the expected sign is negative whereas for vertical differentiation, the sign should be positive. The rationale is that a greater dispersion in unit value ratios within an industry should be associated with greater potential for product differentiation. The limitation with this measure in services is that unit values are not available.

The third measure of product differentiation is the intensity in research and development and sales techniques in different industries. New varieties of products/services must be developed through R & D and be marketed so that consumers are aware of them. The following proxies are used for differentiation: ratio of R& D, purchased advertising, marketing and sales costs to total sales. It is assumed that IIT varies positively with these variables.

The fourth measure used is the proportion of non-manufacturing, professional, or technical staff in total employment of an industry. Generally, the lower the manufacturing employment relative to total employment, the higher the product/service differentiation since these staff are deemed necessary to differentiate their products/services from those of competitor firms.

5.2.2.2 Economies of scale

This is the basis of most theories of IIT and measures the degree of decreasing costs in an industry/firm. In most trade models, price differentials between countries in intra-industry product lines are used to proxy scale economies. It is assumed that there is a positive relationship between IIT and the size of the firm/industry.

There are two measures of economies of scale. The first measure is the minimum efficient scale of production commonly proxied by the average firm size or the value-added in the industry. The second measure is the degree of capital in production. The third measure is the share of employment in firms with greater than 500 employees and finally the relative productivity of large firms. Other studies use combinations of these measures.

5.2.2.3 Market structure

Industrial organisation literature (e.g. Spence, 1976) emphasized that product differentiation is likely to be at maximum under conditions, which approximate monopolistic competition. Lancaster (1980) argues that IIT will be at a maximum under conditions of "perfect monopolistic competition". Perfect competition and oligopolistic market structures also play some role.

The number of firms in an industry or the concentration ratio, the market share of the top j firms in the industry is quite important. The market share can be measured using a Herfindal index, which is obtained by squaring the market share of the various players and then summing those shares.

5.2.2.4 Product/service life cycle

The longer a product/service has been manufactured, the higher the potential for differentiation and hence IIT. Differentiation can take two forms; differentiation by attributes and technology/quality. The life cycle emanates from three sources. Firstly, it takes time to develop varieties of a product/service before differentiation can take place. Secondly, product cycle leads to the potential for import and export of various vintages of the same product/service. Finally, there can be trade in vertically (quality) differentiated products/services. The product life cycle is measured as the age of a product/service multiplied by the number of patents in the industry.

5.2.2.5 Multinational corporations

The relationship between the role of multinational corporations and IIT is a controversial issue. On one hand, the activities of multinational corporations may be associated with high-unaffiliated IIT. Markusen (1994), Markusen and Venables (1998, 2000) extended the trade theories of IIT in the presence of FDI developed by Helpman and Krugman in the 1980s. They argue that FDI positively contributes to the volume of IIT and therefore any IIT model should take into account the positive contribution of FDI. Markusen and Venables (1998,2000) note that MNC overcome the costs of trade barriers by establishing themselves in the host countries and then generating arms-length trade with the source country.

On the other hand there can be a negative relationship between IIT and the activities of the multinational corporations. This is predicated on the fact that since firms may serve foreign markets directly rather than through trade, FDI may be a substitute for unaffiliated IIT.

The intensity of multinational corporation activity is measured by the percentage of sales accounted for by multinational corporations or FDI at the industry level.

5.2.3 Econometric modeling of IIT

Most econometric studies of the determinants of IIT employ the ordinary least squares (OLS) or its variants. The Grubel and Lloyd index, most commonly used in empirical studies, varies between 0 and 1 and OLS may provide forecasts, which are not within the 0 to 1 interval. This problem, is corrected by the following logistics transformation:

$$\ln\left(\frac{IIT}{1-IIT}\right) \tag{5.4}$$

This difficulty is also faced in studies that attempt to disentangle IIT into horizontal and vertical product differentiation and use the share that these classifications take in total trade. Balassa and Bauwens (1987: 1426) point out that the specification in Equation 5.4 cannot handle cases where IIT is either 0 or 1 since the natural logarithms of these values do not exist. In order to incorporate these values into the estimation, they recommend a nonlinear logistics transformation of the form;

$$IIT = \frac{1}{1+e^{-\beta' z}} + \varepsilon \qquad (5.5)$$

Where z is a matrix of explanatory variables. This estimation procedure preserves the valuable information provided by the 0 and 1. It is, however, important to note that Equation 5.5 is the inverse of Equation 5.4.

5.3 EMPIRICAL LITERATURE ON THE DETERMINANTS OF IIT IN SERVICES

Most of the empirical studies of IIT have been restricted to trade in goods. However, there are a few studies dealing with services trade. Tang (1999), using game-theoretic approach, shows that the GL index and industry characteristics hold under the assumption of Bertrand-Nash competition. The study employs panel data to explain bilateral telephone traffic between the US and 146 foreign destinations during the period 1990-97.

The study finds that there is decreasing share of IIT in telephone traffic between the US and foreign destinations and this trend is explained by larger country-specific differentials in cost, tele-density, market concentration and other control factors.

Lee and Lloyd (2002) conduct an empirical analysis of inter-country differences in IIT in services in the OECD. They examined the effect of the inclusion of trade in services on observed level of IIT in goods and services combined. The study found that IIT was uniformly high in twenty OECD countries and nine service industries, and also stable over time. However, for seventeen out of the twenty countries, combining goods and services trade reduces the magnitude of trade imbalance. This in turn raises the level of IIT because of the negative empirical relationship between the level of IIT and trade imbalance.

Li, Moshirian and Shim (2003) measured the extent of IIT for insurance services for the US with her trading partners in 1995 and 1996. The study took into account the role of

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FDI as well as openness in generating IIT. Furthermore it improved the previous methodology employed in the IIT literature by using two-stage least squares (2SLS) and two-stage non-linear logit (2SNL) model as opposed to the use of either the OLS or the simple logit model, which create simultaneity and measurement errors.

The study found that the IIT model of insurance services captured the key factors that are important in increasing the volume of IIT in insurance services. Firstly, there is a positive role of FDI in contributing to an increase in the volume of IIT. This supports the new trade theories that emphasise the role of multinational corporations (MNC) in complementing the increase in the volume of trade rather than as a substitute for trade. Secondly, the paper found that trade intensity between the US and her trading partners contributes to the existence of product differentiation in insurance services and hence an increase in consumer welfare. Thirdly, the difference in the openness of domestic market between the US and her trading partners negatively influences the degree of IIT. The authors argue that this is because of the greater number of opportunities of the insurance companies' products leading to a higher degree of IIT.

To the best of our knowledge there is no study on IIT in services in South Africa. Indeed, in South Africa, the few studies on IIT have focussed on merchandise trade (e.g. Isemonger, 2000 and Peterson, 2002).

5.4 MODEL SPECIFICATION FOR THE SOUTH AFRICA-US IIT IN UNAFFILIATED SERVICES

In constructing the model, "country-specific" and "industry specific" determinants of bilateral IIT in services are combined in one equation. The basic equation (with predicted signs) is;

$$IIT_{it} = f(\overset{+}{IIT}_{it-1}, \overset{-}{P}_t, \overset{-}{S}_{it}, \Delta\overset{+}{E}_t, \overset{+}{D}SA_{it}, \overset{-}{TSA}_{it}, \overset{+}{TUS}_{it}, \overset{-}{FI}_{it},) \tag{5.6}$$

IIT_{it} is the unadjusted GL index for IIT in unaffiliated[19] services calculated as in Equation 5.7.

$$IIT_{it} = 1 - \frac{|X_{it} - M_{it}|}{X_{it} + M_{it}} \text{ or } IIT_{it} = \frac{2Min(X_{it}, M_{it})}{X_{it} + M_{it}}, IIT_{it} \in [0,1], \forall_{i,t} \quad (5.7)$$

Where X_{it} and M_{it} are nominal value of exports and imports (US \$) of unaffiliated services, respectively. P_t is an index of difference in per capita income between South Africa and US (used as a proxy for dissimilarities in demand structure/economic distance). S_{it} is an index of difference in market size between the US and South Africa and is used as a proxy for economies of scale. ΔE_t is the change in nominal rand-US dollar exchange rate (rand/ US$). DSA_{it} is an index of the degree of economic freedom (deregulation) in South Africa. TSA_{it} and TUS_{it} are Hoekman (1995)-type services trade openness indices in terms of market access and national treatment for all modes of supply in South Africa and the US respectively. They are computed in Chapter 4. FI_{it} is the US foreign direct investment (FDI) in South Africa.

The subscript *i* denotes the *i*th service sector [*i*=airfreight services; education services; financial services; legal services; management, consulting and public relations services; ocean freight services; ocean port services; research & development, and testing services (royalties and fees); telecommunication services and travel (tourism) services]. The subscript t denotes the *t*th year (*t*=1994, 1995,…,2002).

Model 5.6 is estimated in the form of Equation 5.4 as follows;

$$y_{it} = \alpha + \beta_1 y_{it-1} + \beta_2 P_t + \beta_3 S_{it} + \beta_4 \Delta E_t + \beta_{i5} DSA_{it} + \beta_6 TSA_{it} + \beta_7 TUS_{it} + \beta_8 FI_{it} + \varepsilon_{it} \quad (5.8)$$

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[19] This is trade flow, which does not involve related parties. For instance service trade between Coca Cola South Africa and its parent company in the US is excluded.

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Where $y_{it} = \log\left(\frac{IIT_{it}}{1 - IIT_{it}}\right)$. This specification makes it possible to conduct hypotheses tests using bootstrapping. Specifying the model in form of Equation 5.5 would entail estimating non-linear equations, which makes bootstrapping a difficult process since non converge terminates the resampling. The different postulations of hypothesis 1 in Section 1.6 of Chapter 1 are specified in Equation 5.9.

$$\beta_1 > 0, \beta_2 < 0 / B_2 > 0, \beta_3 < 0, \beta_4 >, \beta_{i5} > 0, \beta_6 < 0, \beta_7 > 0, \beta_8 < 0 \tag{5.9}$$

The disturbance term is specified as a two-way error component model;

$$\varepsilon_{it} = \mu_i + \lambda_t + \nu_{it} \tag{5.10}$$

Where μ_i denotes service-specific effects, λ_t denotes year-specific effects, and ν_{it} is idiosyncratic disturbance, which varies across services and time. No normality assumption is made about this error term in finite samples since nonparametric bootstrapping techniques are used in statistical inference[20].

The service-specific effects and time-specific effects can either be treated as fixed or random. There are two approaches to distinguishing these two effects. The first approach is the randomness of the unobserved effects. In this regard, "random effect" is treated as random variables while "fixed effect" is considered non-stochastic parameters to be estimated for each cross-section, using dummy variables.

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[20] Asymptotic normality assumption still holds since the Edgeworth expansion as presented for instance in Hall (1992:83), uses the cumulative normal distribution as the first term;

$G(x) = P(T \leq x) = \Phi(x) + n^{-\frac{1}{2}} q(x)\phi(x) + O(n^{-1})$. Where $T = n^{1/2}\left(\hat{\beta} - \beta\right) / \hat{\sigma}$ is a pivotal statistic, which is asymptotically normally distributed, q is an even quadratic polynomial and Φ, ϕ are standard cumulative normal distribution and density functions respectively. The notation "$O\left(n^{-1}\right)$" denotes a random variable that is of order n^{-1}.

The second approach is to use the correlation of the unobserved effects with observed explanatory variables, a method suggested by Mundlak (1978) and underscored by Wooldridge (2002). In this regard, "random effect" is assumed if there is zero correlation between the observed explanatory variables and the unobserved effects;

$$Cov(z_{it}, \mu_i) = 0, Cov(z_{it}, \lambda_t) = 0 \tag{5.11}$$

Where z_{it} is a matrix of explanatory variables in Equation 5.8. On the contrary, fixed effects paned data model allows for arbitrary correlation between the unobserved effects (μ_i and λ_t) and the observed explanatory variables (z_{it}).

A fixed effect model is used in the study because the focus is on specific set of service sectors and inferences are restricted to the behaviour of these service sectors. Moreover, correlation between unobserved effects and observed explanatory variables is allowed.

The service-specific effects (μ_i) are assumed fixed parameters to be estimated and they represent any *unobservable* service-specific characteristics that do not vary over time. These characteristics relate to the nature of specific services such as non-storability, heterogeneity and high flexibility/customisation, imperfect competition, and asymmetric information (coupled with adverse section and moral hazards). Specifically, these may include the following;

(i) The different modes of supply. For instance, education and travel services are mainly supplied through mode 2 (consumption abroad) as opposed to telecommunications services basically supplied through mode 1 (cross-border trade)

(ii) Degree of service differentiation/service delivery

(iii) The level of information asymmetry in the service sector

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(iv) Other service-specific issues such as unobservable management capabilities/styles, level of trust, politics/government influences etc., which apply to specific service sectors

The time-period effects (λ_t) are also assumed fixed parameters to be estimated as coefficients of time dummies for each year in the sample. These effects are service-sector invariant and can be justified given the numerous policy interventions as well as events in South Africa and the US. The service sector invariant events may include, among others, the following;

(i) South Africa's new political dispensation in 1994, which created new trading conditions that cut across all the services

(ii) The effects of the East Asian crisis in 1997 and Russian financial crisis in 1998

(iii) The September 11 bomb blast in the US

5.5 DATA DESCRIPTIONS

The following data are used for estimation. IIT_{it}: Mirrored[21] unaffiliated services trade data are used to compute South Africa-US unadjusted GL index. The data is taken from the United States Bureau of Economic Analysis (http://www.bea.gov/bea/di/1001serv/intlserv.htm). The IIT is computed using Equation 5.7. The data is in nominal US dollars (millions) and is not deflated due to lack of sectoral deflators. Additionally, since the GL index is homogenous of degree zero, there is no difference between the index computed using nominal and real data.

In view of the fact that there are some observations with IIT exactly equal to 0 or 1, these were adjusted by adding US dollars 0.00001 millions to the sectoral exports and imports.

[21] Mirrored refers to the fact that data is collected from the trading partner's side. This means that US imports are treated as South Africa's exports and vice versa. There are limitations in this approach such as under–invoicing. However, it is hoped that the US has an efficient system of recording international transactions.

In some services, the US BEA does not disclose data for some years. In these instances, interpolation is used.

P_t : Nominal GDP per capita (US \$) for South Africa and US is collected from the IMF's International Financial Statistics. Instead of taking absolute values of inter-country differences in per capita incomes, Balassa (1986) index shown in Equation 5.1 is used to calculate relative differences that take values between 0 and 1.

S_{it} : Data used to calculate differences in market size was collected from different sources. Proxies for market size variable differ from service to service as shown in Table 5.1.

Table 5.1: Proxies for market size

Service	Proxy of market size	Source
Air freight	Air transport freight (million tons per KM)	World Development Indicators
Education	South African students enrolled in US tertiary institutions and vice versa	Open Doors. http://opendoors.iienetwork.org/
Financial services	Foreign assets of banking and financial institutions	IMF International Financial Statistics
Legal services	Civil cases of debt	STATSSA and US Federal Court
Management, Consulting and public relations	Data on other services in UNCTAD services trade data	UCTAD
Ocean freight	Merchant shipping fleets: total (000 gross registered tons)	UN Statistical Yearbook
Ocean port services	Merchant shipping fleets: total (000 gross registered tons)	UN Statistical Yearbook
Research & Development, and Testing services	Trademarks and patents granted	World Intellectual Property Organisation (WIPO) http://www.wipo.int
Telecommunications	Fixed telephone lines and mobile subscribers per 1000 people	World Development Indicators
Travel	Number of tourist arrivals	World Development Indicators

Source: Different sources as indicated in the last column

Instead of taking absolute values of inter-country differences in market size, Equation 5.1 is used to calculate a measure indicating relative differences that takes values between 0 and 1. The use of this index solves two problems. Firstly, it is not affected by magnitudes of particular country characteristics. This is indeed very important when comparing US (large country) with South Africa (small country). Secondly, this index circumvents the problem of differences in units of measurements for the proxies of market size across the service sectors.

ΔE_{it}: The change in rand-US dollar exchange rate (rand/$). The data is collected from the IMF International Financial Statistics.

DSA_{it}: Index of economic freedom published by the Fraser Institute (**http://www.freetheworld.com/**) is used as a proxy to measure the degree of deregulation in a particular service sector in South Africa.

The index measures the degree of economic freedom present in five major areas;
(i) Size of government: Government consumption, transfers and subsidies, government enterprises and investment, top marginal tax rate (income tax and payroll tax).
(ii) Legal structure and security of property rights: Judicial independence; impartial courts; protection of intellectual property; military interference; and integrity of the legal system.
(iii) Access to sound money: Growth of money supply; inflation variability; freedom to own foreign currency.
(iv) Freedom to exchange with foreigners: Taxes on international trade (as percentage of exports and imports, mean tariff rate and variability of tariff rates); regulatory trade barriers (hidden import barriers, cost of importing); size of trade sector; restrictions on capital markets (access to foreign capital, restrictions on foreign capital transactions)
(v) Regulation of credit, labour and business: Regulation of credit markets (private ownership of banks, competition from foreign banks, extension of credit to private sector, avoidance of negative real interest rates); regulation of labour markets (impact of minimum wage, flexibility in hiring and firing, collective bargaining, incentives for unemployment benefits, military conscription); regulation of business (price controls, administrative obstacles to new businesses, time spent with government bureaucracy, ease of starting a new business, irregular payments to government officials).

On a scale of 0 to 10, the measure gives a higher value to the country where there is limited state regulation on economic activity.

TSA_{it} *and* TUS_{it}: Indices of trade openness in the services sector and are constructed using the Hoekman approach (Chapter 4). This is to some extent related to the economic freedom index. However, these indices are more specific to international trade in services.

Table 5.2: Degree of deregulation (economic freedom)

Service sector	**Proxy for the degree of deregulation**
Air freight services	Regulatory trade barriers
Advertising	Restrictions to exchange with foreigners
Education and training services	Country overall rating of economic freedom by the Fraser institute
Financial services	Access to sound money
Legal services	Integrity of the legal system
Management consulting and public relations Services	Freedom to exchange with foreigners
Other business, professional and technical services	Restriction on foreign capital transactions
Ocean freight services	Regulatory trade barriers
Ocean port services	Regulatory trade barriers
Research & development and testing services	Protection of intellectual property rights
Telecommunication services	Freedom to exchange with foreigners
Travel services	Country overall rating of economic freedom by Fraser institute, Canada

Source: Fraser Institute, **http://www.freetheworld.com/**

FI_{it}: Mirrored sectoral FDI (US $ millions) is collected from the US Bureau of Economic Analysis. FDI includes the initial transaction between two entities and all subsequent financial transactions between them and among affiliated enterprises, both incorporated and unincorporated. Position of total and sectoral US FDI abroad is used to compute a ratio as follows;

$$FI_{it} = \frac{FDI_i}{FDI_t} \tag{5.12}$$

Where FDI_i is the position of US FDI in South Africa in sector *i*, FDI_t is the position of US total foreign direct investment in South Africa.

5.6 THE ESTIMATION METHODS

5.6.1 The Estimation of the dynamic panel data model

The panel data model in Equation 5.8 is estimated within a general linear model (GLM) framework. GLM is an extension of the multivariate regression model in a number of ways. Firstly, the GLM allows for linear transformation or linear combinations of multiple dependent variables. This provides the ability to analyse effects or repeated measures and thus encapsulate panel data model. Secondly, since GLM uses generalised inverse, it can provide solution to normal equations when the regressors are linearly dependent. The following assumptions are made.

Firstly, there is strict exogeneity of explanatory variables conditional on unobserved effects;

$$E\left(\nu_{it} \middle| z_{it}, \mu_i, \lambda_t\right) = 0 \qquad (5.13)$$

Secondly, the fixed effects estimator is well behaved asymptotically if the standard rank condition on a matrix of time-demeaned explanatory variables holds;

$$rank\left(\sum_{t=1}^{T} E\left(\ddot{z}_{it}' \ddot{z}_{it}\right)\right) = rank\left[E\left(\ddot{z}_i \ddot{z}_i\right)\right] = K \qquad (5.14)$$

Where $\ddot{z}_{it} = z_{it} - \bar{z}_i$ and K is the number of regressors. This assumption shows that time-constant variables such as distance should not be used in fixed effects analysis unless they are interacted with time varying variables (Wooldridge, 2002).

The fixed effects estimator is;

$$\hat{\beta} = \left(\sum_{i=1}^{N} \ddot{z}_i' \ddot{z}_i \right)^{-1} \left(\sum \ddot{z}_i' \ddot{y}_i \right) = \left(\sum_{i=1}^{N} \sum_{t=1}^{T} \ddot{z}_{it}' \ddot{z}_{it} \right)^{-1} \left(\sum_{i=1}^{N} \sum_{t=1}^{T} \ddot{z}_{it}' \ddot{y}_{it} \right) \tag{5.15}$$

Where $\ddot{y}_{it} = y_{it} - \bar{y}_i$

Equation 5.15 is a WITHIN estimator because it uses the time variation within each service-sector. However, it provides the same results as a least squares dummy variable (*LSDV*) model where demeaning is not done first.

The third assumption is that the fixed effects estimator has a constant variance

$$E\left(v_i' v_i \middle| z_i, \mu_i\right) = \sigma_v^2 I_T \tag{5.16}$$

This assumption in effect implies that the idiosyncratic errors have constant variance across t and serially uncorrelated. It then follows that $\sqrt{N}\left(\hat{\beta} - \beta\right) \sim N\left(0, \sigma_v^2 [\ddot{z}_i' \ddot{z}_i]^{-1}\right)$.

The asymptotic variance is $A\text{var}(\hat{\beta}) = \hat{\sigma}_v^2 \left(\sum_{i=1}^{N} \sum_{t=1}^{T} \ddot{z}_{it}' \ddot{z}_{it} \right)^{-1}$ (5.17)

In this case $\hat{\sigma}_v^2 = \dfrac{SSR}{\left[N(T-1) - K\right]}$ (5.18)

Where $\hat{\sigma}_v^2 = \sum_{i=1}^{N} \sum_{t=1}^{T} \hat{v}_{it}^2$

The problem is that the usual standard errors from the regression in Equation 5.8 are too small on average because they use an incorrect estimate of σ_v^2. To correct for this problem, Wooldridge (2002) recommends that each standard error be multiplied by the factor;

$$\left\{ \frac{(NT - K)}{\left(N(T-1) - K\right)} \right\}^{1/2} \tag{5.19}$$

Since y_{it} in Equation 5.8 is a function of μ_i and λ_t in several ways, y_{it-1} is also a function of these variables. This implies that the assumption of exogeneity in Equation 5.13 is violated. Baltagi (2001) argues that the endogeneity problem renders the OLS estimator biased and inconsistent even if v_{it} are not serially correlated.

With moderate time dimension, the bias of LSDV estimator can be substantial. Nickell (1981) analytically derives three different possibilities of bias on the coefficient of the lagged dependent variable. Firstly, it is negative if the population value of this coefficient is positive. Secondly, it is increasing in the value of the population parameter and finally the bias does not disappear when the cross-section dimension (N) grows large.

Alternative dynamic panel estimators are the first differenced generalised method of moments (GMM) estimator of Arellano and Bond (1991) and the system GMM estimator of Arellano and Bover (1995). These estimators are conceived for panel data models when the time dimension is large relative to N. i.e. $N \to \infty$.

Kiviet (1995) derived an approximation of the bias of the WITHIN estimator in a dynamic panel data model with serially uncorrelated disturbances and strongly exogenous regressors. This method subtracts consistent estimator of the bias from the original WITHIN estimators.

Everaert and Pozzi (2004) attempted to introduce an iterative bootstrap algorithm as an alternative for the analytical bias correction proposed by Kiviet (1995). Starting from the biased LSDV estimates, their method entailed searching over the parameter space for the unknown population parameters. These coefficients can then be considered to be unbiased estimates for the true parameters.

The study uses bootstrap-based bias correction to deal with the problems of endogeneity as well as heteroscedasticity. The bootstrap-based approach is in the spirit of Everaert and Pozzi (2004) in dealing with endogeneity.

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5.6.2 The design matrix

5.6.2.1 Overparameterised model

This is also referred to as the "indicator variable" approach. In this method a separate predictor variable is coded for each group identified by a categorical predictor variable. This method will almost always lead to $X'X$ matrices with redundant columns, thus require generalized inverse for solving the normal equations. It is as a result of this characteristic that this method is called overparameterised model for representing categorical predictor variables.

5.6.2.2 Sigma-restricted model

This model uses the convention that the effects must sum to zero. This constraint is imposed by coding the variables using combinations of –1, and 1s or any other numbers which in combination will sum up to 0. A reference category must be chosen. Rather than fix the effect of the reference class to 0, the effects will equal 1 minus the sum of the remainder categories, thus ensuring that the effects sum to 0. The sigma-restricted model is used in the thesis.

5.7 STATISTICAL INFERENCE USING CLASSICAL APPROACH

This approach uses first-order asymptotic distribution of the test statistic under the null to approximate Type I critical values[22]. The rationale for this approximation is the fact that most test statistics in econometrics are asymptotically pivotal because their asymptotic distributions do not depend on unknown population parameters when the null hypothesis being tested is true. On the basis of this, an approximate Type I critical value can be obtained from asymptotic distribution theory without knowledge of where the true data generating process (DGP) is in the set specified by the null hypothesis.

[22] This is Type I error, which is committed when one rejects a true null hypothesis.

Classical statistical inference entails the following procedure. Firstly, an assumption is made that the estimated statistic's sampling distribution has a shape with known probability properties (e.g. normal distribution in most regression models). In regression analysis, the OLS estimates will be normally distributed if the model's error is normally distributed i.e. $\hat{\beta}|X \sim N\left(\beta, \sigma_{\varepsilon}{}^{2}\left(X'X\right)^{-1}\right)$ (Green, 2003:50).

Secondly, the parameters of the model are estimated analytically using Equation 5.20.

$$\hat{\beta} = \left(X'X\right)^{-1}\left(X'Y\right),\ \hat{\sigma}_{e}^{2} = \frac{e'e}{N-K} \tag{5.20}$$

Once $\hat{\beta}$'s sampling distribution is deduced using the parametric assumption and the analytic formulas associated with it, statistical inferences can be drawn about β.

The hypothesis testing in the classical procedure seeks evidence in the sample to refute the "null" hypothesis. This is done using the Neyman-Pearson methodology (Green, 2003:153-154). In this methodology, the null is usually cast as the narrowest model in the set under consideration. The problem with the Neyman-Pearson methodology is that a sharp conclusion cannot be reached. Unless the significance level of the testing procedure is made so high as to exclude all alternatives, there will always remain the possibility of a Type I error. Consequently, the null is never rejected with certainty, but only with a stated degree of confidence.

However, as pointed out by Horowitz and Savin (2000) and Horowitz (2001), Monte Carlo experiments show that first-order asymptotic theory often gives a poor approximation to the distribution of test statistics with the samples used in most econometrics applications. Consequently, the true nominal probabilities that a test makes a Type I error can be very different when an asymptotic critical value is used (Error rate probability/coverage error).

5.8 STATISTICAL INFERENCE USING BOOTSTRAPPING

Bootstrap methodology, introduced by Efron (1979), provides a good estimator of the true Type I critical values that are more accurate than the approximation of first-order asymptotic theory (Horowitz and Savin, 2000, Horowitz, 2001). According to Mooney and Duval (1993: 1), bootstrapping uses the analogy between the sample and the population from which the sample was drawn. It involves "resampling" either the data or the error term with replacement many times in order to generate an empirical estimate of the entire sampling distribution of the parameters.

The bootstrap allows inferences to be made without making strong distributional assumptions and without the need for analytic formulas for the sampling distributions of parameters. Instead of imposing a shape on $\hat{\beta}$'s sampling distribution by assumption, bootstrapping entails empirically estimating its entire sampling distribution by examining the variation of the statistic in the bootstrap sample.

Bootstrapping uses the same model structure as the classical approach and the only difference is the inferential foundation. The corollary of this is that bootstrapping is not useful in improving the estimation of a parameter, but rather in testing its statistical properties.

The basic bootstrap approach is to treat the sample as if it is the population and apply Monte Carlo sampling to generate an empirical estimate of the statistic's sampling distribution. This is done by drawing a large number of resamples of size n from the original sample of size n randomly with replacement[23]. Despite the fact that each resample would have the same number of elements as the original sample, through resampling with replacement each resample could have some of the original data points represented in it more than once and some not represented at all. Consequently, each of this resamples will likely be slightly and randomly different from the original sample.

[23] The Jackknife method entails sampling without replacement.

Since the elements in each resample vary slightly, a statistic $\hat{\beta}^*$ calculated from one of this resamples will likely take on a slightly different value from each of the other $\hat{\beta}^*$'s and from the original $\hat{\beta}$. The central point in bootstrap is that a relative frequency distribution of these $\hat{\beta}^*$'s calculated from the resamples is an estimate of the sampling distribution of $\hat{\beta}$.

5.8.1 Theoretical justification of bootstrapping

Mooney and Duval (1993) provide a non-technical justification of bootstrapping. They argue that the bootstrapping procedure is based on two analogies. Firstly, the analogy of the sample empirical distribution function (EDF) and the population distribution function (PDF) that generated the data. Secondly, the analogy between the random resampling mechanism with the stochastic component of the model. In the regression framework, the error term should not have serial correlation and heteroscedasticity.

These two analogies are predicated on two levels of asymptotic theory. Firstly, as the original sample size (n) approaches the population sample size (N), the EDF $\hat{F}(x)$ approaches the true distribution, F(X). This simply reiterates the point that as a sample increases in size, it contains more and more information about the population until n=N, in which case $\hat{F}(x) = F(X)$. Secondly, the bootstrapped sampling distribution $\hat{F}^*(\hat{\beta}^*)$, approximates $F(\hat{\beta})$ in a given sample when n is large enough to allow $\hat{F}(x)$ to approach F(X). Under these conditions, as the number of resamples (B) increases to infinity, $\hat{F}^*(\hat{\beta}^*) \approx F(\hat{\beta})$.

A more detailed asymptotic theory of bootstrap is presented in Hall (1992), and Hall (1994) and relies on Edgeworth and Cornish-Fisher expansions in order to prove the existence of asymptotic refinements.

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5.8.2 Factors that hamper the performance of bootstrap methodology

There are situations when bootstrap methodology performs worse than the classical approach. These situations emanate from the theoretical justification of bootstrapping.

Firstly, when the EDF is not a good approximation of the PDF. In this case the bootstrapped estimate of the sampling distribution of $\hat{\beta}$ will be inaccurate. Mooney and Duval (1993) point out that this lack of congruence between the EDF and PDF could emanate from a small sample, a biased sample design or merely random bad lack.

Secondly, there is a limitation in using EDF as an estimate of density of PDF, which could affect the accuracy of the bootstrap results. This problem, pointed out by Mooney and Duval (1993), relates to the fact that the PDF is continuous while the EDF is always a discrete function. The effect of this is that between the steps of the EDF are values of the PDF that cannot be included in the analysis. If those values included and left out of the EDF are evenly and randomly distributed, this should not affect the accuracy of the results. However, if this is not the case (e.g. with small and biased sample), the accuracy of the bootstrap could be impaired.

Thirdly, the presence of serial correlation could affect the accuracy of bootstrapping. If the bootstrap is to work well, the bootstrap error terms should display the same sort of serial correlation as the structural errors (Mackinnon, 2002, Efron and Tibshirani, 1993). The problem is that in applications, it may not be clear how the real error terms are generated. Mackinnon (2002) points out that there are two approaches followed. The first approach, which is semi-parametric in nature, is "sieve bootstrap"**.** A unit root null is first imposed and an autoregressive model of order p is estimated. In this case p is chosen in a way that it increases with the sample size. Resampling the rescaled residuals from the autoregressive model then generates new innovations. The serially correlated bootstrap error terms are constructed from the model and the innovations. The second approach, which is fully nonparametric, is to resample groups of residuals. One of the simplest of such methods is the "block bootstrap", proposed in various forms by Carlstein (1986), Efron and Tibshirani (1993), and Politis and Romano (1994), among others.

Fourthly, models with heteroscedasticity reduce the power of bootstrapping (Davison and Hinkley, 1998, Mackinnon, 2002, and Flachaire, 2003). This is a serious problem in this study since the different service sectors are likely to have different error variances. Davison and Hinkley (1998) note that if heteroscedasticity can be modelled, then bootstrap simulation by resampling errors is still possible. Since heteroscedasticity is a potential problem in this thesis, Section 5.8.3 presents a detailed discussion about it.

5.8.3 Heteroscedasticity and bootstrapping

The standard error components model given in Equation 5.8 assumes that the regression disturbances are homoscedastic with the same variance across time and individual service sectors. This is a restrictive assumption in South Africa-US IIT in services, which covers diverse service sectors.

Baltagi (2001) points out that assuming homoscedastic disturbances when heteroscedasticity exists will result in consistent estimates of the regression coefficients but the estimates will not be efficient. Additionally, the standard errors of these estimates will be biased unless a robust standard error is computed, which corrects for the possible presence of heteroscedasticity.

White (1980) proposed heteroscedasticity consistent covariance matrix estimator, (HCCME), which permits asymptotically correct inference on the parameter estimates in the presence of heteroscedasticity of unknown form. Mackinnon and White (1985) considered a number of possible forms of HCCME, and showed that, in small samples, the t and F statistics based on them can be seriously biased. Chester and Jewitt (1987) showed that the extent of the bias is related to the structure of the regressors, and specifically the presence of observations with high leverage.

Within a panel data framework, heteroscedasticity can be present in the service-specific effects [$\mu_i \sim iid(0,\sigma_\mu^2)$ in Equation 5.10) as first suggested by Mazodier and Trognon (1978), the remainder error term [$\nu_{it} \sim iid(0,w^2)$ in Equation 5.10] or both. This study uses fixed effects model and it is assumed that the service-specific effects are homoscedastic.

The problem with these corrections is that they suffer from small size bias distortions and bootstrap methods could be used to approximate the finite-sample distribution of test statistics under the null hypotheses. In order for bootstrap methods to be reasonably accurate, it is important that the data generating process (DGP) used for drawing samples should be as close as possible to the true DGP that generated the observed data, while making the assumption that the DGP satisfies the null hypothesis. However, presence of heteroscedasticity reduces the power of bootstrapping (Davison and Hinkley, 1998, Mackinnon, 2002 and Flachaire, 2003). Davison and Hinkley (1998) note that if heteroscedasticity can be modelled, then bootstrap simulation by resampling errors is still possible.

The problem is when the form of heteroscedasticity is unknown. In this case bootstrap samples must be generated in such a way that the relationship between the variance of each error term and the corresponding regressors is retained. The simplest way of dealing with heteroscedastic errors, which was originally proposed by Freedman (1981), is called "pairs bootstrap". The idea of bootstrapping pairs is to resample the regressand and regressors together. In this approach the assumption of nonstochastic regressors in Equation 5.13 is dropped. The problem with this methodology is that it could mess up the design matrix.

The second way to deal with heteroscedasticity of unknown nature is to use "wild bootstrap", which was proposed by Liu (1988) following the work of Wu (1986) and Beran (1986). Wild bootstrap estimates variances from the individual residuals (Davison and Hinkley 1998: 272). Liu established the ability of the wild bootstrap to provide refinements for the linear regression model with heteroscedastic errors and further evidence was provided by Mammen (1993), Davidson and Flachaire (2001) and Flachaire (2003). Mammen showed that under some regularity conditions, wild bootstrap is asymptotically justified in the sense that the asymptotic distributions of the various statistics are the same as the asymptotic distributions of their wild counterparts. To perform wild bootstrap, the following algorithm is used.

(i) For ε_{it}, where i is the service sector and $t = 1994,1995,....,2002$
(ii) Modify the residuals using any of the methods in Equations 5.21,15.22 and 5.23.
(iii) Generate one of the two-point (lattice) distributions in Equation 5.24 or 5.25.
(iv) Resample from the distribution in (iii) with replacement to generate t_{it}
(v) Multiply the modified residual with resampled two-point distributed variable to $v_{it}^* = a_{it} e_{it} t_{it}$
(vi) Generate response function as follows $y_{it}^* = X_{it}\hat{\beta} + v_{it}^*$
(vii) Fit least squares to $(x_{i1}, y_{i1}^*),.....(x_{in}, y_{in}^*)$ giving estimates of parameters and standard errors.
(viii) Repeat steps (i) to (vii) B times.
(ix) Get empirical distribution function for parameter estimates by placing a probability of 1/B at each value. Construct confidence intervals using percentile, Bias Corrected, etc methods.

Mackinnon and White (1985) showed the possible forms of a_t;

$HC_{i0} : a_{it} = 1$ i.e. no transformation of errors

$$HC_{i1} : a_{it} = \sqrt{\frac{n}{n-k}} \tag{5.21}$$

Where n is the sample size and k is number of parameters estimated. The rationale for this heteroscedastic consistent transformation is the fact that OLS residuals have smaller variance than the error terms on which they are based. In a panel framework, the equivalent version is Equation 5.19.

$$HC_{i2} : a_{it} = \frac{1}{\sqrt{1-h_{it}}} \tag{5.22}$$

Where $h_{it} = X_{it}(X'X)^{-1}X'_{it}$, the leverage is the jth element of the orthogonal projection matrix on to the span of the columns of X.

$$HC_{i3} : a_{it} = \frac{1}{1-h_{it}} \tag{5.23}$$

The popular method is the two-point distribution suggested by Mammen (1993);

$$F_1 : t_{it} = \begin{cases} -(\sqrt{5}-1)/2, with \quad probability & \frac{(\sqrt{5}+1)}{2\sqrt{5}} \\ (\sqrt{5}+1)/2, with \quad probability & \frac{(\sqrt{5}-1)}{(2\sqrt{5})} \end{cases} \tag{5.24}$$

Another simpler two-point distribution is called the Rademacher distribution

$$F_2 : t_i = \begin{cases} -1, with \quad probability & \frac{1}{2} \\ 1, with \quad probability & \frac{1}{2} \end{cases} \tag{5.25}$$

Davidson and Flachaire (2001) show that, on the basis of theoretical analysis and simulation experiments, wild bootstrap tests based on the Rademacher distribution, F_2, will usually perform better in finite samples than ones based on the F_1.

5.8.4 Estimation of bias in bootstrap methodology

The bootstrapped sampling distribution $\hat{F}^*(\hat{\beta}^*)$ can be used to assess the bias of $\hat{\beta}$ (Mooney and Duval, 1993: 30-33).

$$Bias(\hat{\beta}) = \hat{\beta} - \hat{\beta}_{(.)}^{\ *} \tag{5.26}$$

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Where $\hat{\beta}^*_{(.)} = \dfrac{\sum_{b=1}^{B} \hat{\beta}^*_b}{B}$

Mooney and Duval (1993:33) warn against subtracting the bootstrap estimate of the bias from the sample $\hat{\beta}$ in an attempt to achieve an unbiased estimate of β. The bootstrap bias estimator from a single sample contains an indeterminate amount of random variability along with bias and this may artificially inflate the mean square error (MSE) of $\hat{\beta}$. The point is that bootstrap is useful for developing inferences about populations using sample data and not necessarily for developing point estimates of parameters. If the standard deviation is much greater than the bias, the latter can be disregarded since the random error will overwhelm it. Efron (1982:8) suggests that when the ratio of the estimated bias to the standard error is less than 0.25, the bias of $\hat{\beta}$ is not a serious problem. The bootstrap methodology provides a general method of estimating this ratio, which is not available under the first-order asymptotic-theory based methods.

5.8.5 Bootstrap confidence intervals

The bootstrap confidence interval methods are based on "modified" Neyman-Pearson methodology. These methods include normal approximation, the percentile method, the bias corrected (BC) and the Percentile-t method, among others.

5.8.5.1 The normal approximation method

This method is analogous to the classical approach to constructing confidence intervals. It is highlighted in Mooney and Duval (1993:34-36) and Davison and Hinkley (1998:198-200). This is based on the fact that whenever it is plausible to assume that a statistic is normally distributed, but no analytic standard error formula exists for it, the bootstrapped sampling distribution can be used to estimate the standard error.

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Just as in the classical case, end points are identified on the z or Student's t distribution associated with $\alpha/2$ and $1-\alpha/2$. Standard errors are then used to transform these z and t scores into the metric of the sample by inserting into the classical confidence interval formula:

$$p\left(\hat{\beta} - t_{\alpha/2}\hat{\sigma}^*_{\hat{\beta}} < \beta < \hat{\beta} + t_{\alpha/2}\hat{\sigma}^*_{\hat{\beta}}\right) = 1-\alpha \tag{5.27}$$

The normal approximation method typically requires fewer bootstrap replications than the other bootstrap confidence interval techniques. The main problem with this method is that it fails to take full advantage of the property that $\hat{F}^*(\hat{\beta}^*)$ estimates the whole sampling distribution of $\hat{\beta}$, not just its second moment[24]. The other problem with this method is that confidence interval developed in this way are no better than those developed with classical approach when the normality assumption is violated.

5.8.5.2 Percentile method

This is a nonparametric method and is highlighted in Mooney and Duval (1993: 36-37) and Davison and Hinkley (1998:202-206). This approach takes literally the notion that $\hat{F}^*(\hat{\beta}^*)$ approximates $F(\hat{\beta})$. The method also uses the Neyman-Pearson approach by first selecting a significance level, α. The α-level confidence intervals includes all the values of $\hat{\beta}^*$ between the $\alpha/2$ and $1-\alpha/2$ percentiles of the $\hat{F}^*(\hat{\beta}^*)$ distribution. For instance, the endpoints of $\alpha = 0.05$ for $\hat{\beta}$ would be the values of $\hat{\beta}^*$ at the 2.5th and 97.5th percentiles of $\hat{F}^*(\hat{\beta}^*)$. To get this, the vector $\hat{\beta}^*$ is sorted in an ascending order and pick the appropriate percentile. For instance, with 1000 resamples, a count up to the 25th value (0.025 times 1000) and count down to the 25th highest value is done.

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[24] A normally distributed variable can be described fully by its two moments only (mean and variance).

The percentile method circumvents the need for the parametric assumption of the classical approach. If the statistic is distributed asymmetrically, it does not adversely affect the accuracy of the percentile method's confidence interval. The percentile method also has the advantage of being simple to execute. Complex formulas are not needed to estimate the parameter $\hat{\beta}$'s assumed sampling distribution, and no critical values for the probabilities of end points on the standardized sampling distribution. The work is simply to calculate $\hat{\beta}^*$, sort them in ascending order and count up and down to appropriate percentiles. It is as a result of this that it is the most widely used method.

There are some limitations of the percentile method. Firstly, as pointed out by DiCiccio and Romano (1988), it may perform poorly with small samples, primarily because of the importance of the tails of the sampling distribution. It may be that large samples are needed to iron out the tails. The second problem with the percentile method is that an assumption that the bootstrapped sampling distribution is an unbiased estimate of $F(\hat{\beta})$ must be made.

5.8.5.3 Bias corrected (BC) method

This method, suggest by Efron (1982), deals with the last problem of the percentile method in Section 5.8.5.2. The details of this method are highlighted in Mooney and Duval (1993:37-40), Efron and Tibshirani (1993: 184), Davison and Hinkley 1998: 203). Instead of assuming that $\hat{\beta}^* - \hat{\beta}$ and $\hat{\beta} - \beta$ are centred on zero (i.e. $\hat{\beta}^*$ is an unbiased estimate of $\hat{\beta}$ and $\hat{\beta}$ is an unbiased estimate of β), the BC method assumes that these quantities are distributed around a constant, $z_0\sigma$. Where σ is the standard deviation of the respective distribution. The quantity z_0 is the biasing constant to be used to adjust the bootstrapped distribution of $\hat{\beta}$.

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The main problem with the BC method is that certain parametric assumptions have to be resorted to. Firstly, it must be assumed that there exists some monotonic transformation of $\hat{\beta}$ and β whose difference has a known distribution, such as normality. Secondly, it assumes that $\hat{\beta}$ is an unbiased estimator of β. This may not make sense in some cases.

5.8.5.4 The Percentile-t method

The details of this method are presented in Mooney and Duval (1993: 40-41). In this approach, the $\hat{\beta}^*$ is transformed into a standardized variable t^*

$$t_b^* = \frac{\left(\hat{\beta}_b^* - \hat{\beta}\right)}{\hat{\sigma}_{\hat{\beta}}} \tag{5.28}$$

The t^*'s are distributed as $\hat{\beta}$ but on a standardized scale. This standardized bootstrap distribution of the estimator is used to develop the critical points in the sampling distribution of $\hat{\beta}$ in a way similar to the Student's t distribution in classical inference. The problem is how to estimate $\hat{\sigma}_{\hat{\beta}}$ so as to convert the $\hat{\beta}^*$'s to t^*'s. The most general approach is "double bootstrap" (Davison and Hinkley, 1998: 223-230).

5.8.5.5 Comparison between bootstrap and classical statistical inference

Table 5.3 shows the difference between bootstrap and classical estimation procedures. The main difference lies on the fact that in bootstrap, the distribution of the parameter is estimated through empirical distribution function (EDF) as opposed to assuming normality. Thus the interpretation of confidence intervals in bootstrap is basically the same as in classical. For instance in a 95 per cent confidence interval, the classical interpretation (i.e.frequentist definition of probability) is that 95 per cent of the confidence intervals will contain the true value while 5 per cent will not.

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There is nothing in classical approach that says that the confidence interval calculated contains the true parameter (Iversen, 1984). It is only hoped that it does. The same interpretation holds for bootstrap. The only difference is that the bootstrap methodology tends to be consistent with frequentist definition of probability since many resamples are done. The Bayesian approach with its bootstrap/resampling versions (such as Gibbs sampling) interprets the same confidence interval differently. The 95 per cent confidence interval means that there is 95 per cent probability that the confidence interval contains the true parameter.

Table 5.3: Bootstrap vs classical inference procedures

Estimation framework	Estimation of parameters	Distributional assumptions	Hypothesis testing
Classical	Any econometric estimation method e.g.GLM	**First-order asymptotic theory** -Central Limit theorem -Normality -Pivotal quantities	**Neyman-Pearson** -Rejection and acceptance regions -Use tabled critical values -Interpretation of confidence intervals consistent with "frequentist" definition of probability as opposed to Bayesian interpretation
Bootstrap	Same as classical. The aim of bootstrap is not to provide point estimates but rather statistical inference	(a)Parametric (b)Nonparametric -EDF approximates PDF -Sample is representative -Use sample to get EDF	**Modified Neyman-Pearson** -Use methods such as Percentile, Normal approximation, Bias corrected(BC), Bias Corrected and Accelerated(Bca), and Percentile t - -Interpretation of confidence intervals consistent with classical

Source: Authors' illustration

5.9 PANEL UNIT ROOT TESTS

The need to test for unit root in panel data emanates from the fact that a regression equation with integrated variables is likely to be spurious (unless there is cointegration).

Panel-based unit root tests have higher power than unit root tests based on individual time series.

Panel-based unit root tests have been advanced by, among others, Qua (1994), Levin and Lin (1993), Maddala and Wu (1999), Hadri (2000), Breitung (2000), Im, Pesaran and Shin (1995, 2003) hereafter referred to as IPS.

The panel unit root tests spring from the following autoregressive process for panel data;

$$y_{it} = \rho_i y_{it-1} + \delta_i x_{it} + \varepsilon_{it} \qquad (5.29)$$

Where $i = 1,2,...,10$ service sectors observed over periods $t = 1994,1995,...,2002$. The variable x_{it} represent the exogenous variables in the model, including any fixed effects or individual trends, ρ_i are the autoregressive coefficients, ε_{it} is identically and independently distributed disturbance term. If $|\rho_i| < 1$ then y_{it} is stationary and if $|\rho_i| = 1$, then y_{it} is nonstationary.

The tests for panel unit roots can be classified into two groups. Firstly, there is a group of tests, which assume that the autoregressive parameters are common across services so that $\rho_i = \rho$ for all i. The Levin, Lin, and Chu (2002), Breitung (2000), and Hadri (2000) tests all employ this assumption. The first two tests employ a null hypothesis of a unit root while the Hadri test uses a null of no unit root.

Secondly, there is a class of tests, which allows ρ_i to vary across the cross-sections (services). The IPS (1995,2003), and the Fisher-ADF and Phillips Perron-based tests (Maddala and Wu (1999) and Choi (2001) all allow for individual unit root processes so that ρ_i may vary across cross-sections. The tests are all constructed by combining individual unit root tests to derive a panel-specific result.

A number of conclusions can be drawn from the unit root tests in Table 5.4. Firstly, the dependent variable, y_{it}, is integrated of order zero implying that the explanatory variables should be I(0). Secondly, a rejection of the null hypothesis by at least one test is used to return a verdict as to whether a variable is I(0) or not. Consequently, all the variables are stationary (except exchange rate) implying that there is no need to proceed to test for panel cointegration.

Table 5.4: Summary of panel unit root test results

	Null: Unit root (homogeneous)		**Null: Unit root (heterogeneous)**			**Null: No unit root (homogenous)**
Variable	*LLC t-stat*	*Breitung t-stat*	*IPS w-stat*	*ADF-Fisher chi square*	*PP- Fisher chi square*	*Hadri z-test*
y_{it-1}	-11.7316 (0.000)**	-1.644 (0.050)	-2.620 (0.004)*	55.361 (0.000)**	70.535 (0.000)*	10.958 (0.000)**
P_t	-71.642 (0.000)**	-1.540 (0.062)*	-15.238 (0.000)*	55.042 (0.000)**	55.042 (0.000)*	2.221 (0.013)**
S_{it}	-187.602 (0.000)**	-0.782 (0.2172)	-52.093 (0.000)**	92.852 (0.000)**	90.7822 (0.000)**	8.105 (0.000)**
FI_{it}	-4.399 (0.000)**	-0.843 (0.199)	0.130 (0.552)	17.922 (0.593)	47.050 (0.001)	7.509 (0.000)**
DSA_{it}	-4.012 (0.000)**	0.883 (0.814)	-0.097 (0.461)	21.044 (0.395)	37.032 (0.012)*	6.281 (0.000)**
ΔE_t	-9.717 (0.000)**	-5.410 (0.000)*	-3.781 (0.000)**	80.258 (0.000)**	163.949 (0.000)*	4.288 (0.000)**
TSA_{it}	-2.529 (0.006)*	-1.741 (0.041)*		6.787 (0.034)*	18.029 (0.586)	
TUS_{it}	-3.594 (0.000)**	-0.471 (0.319)	-0.460 (0.323)	4.215 (0.122)	15.137 (0.001)*	213.220 (0.000)**

Notes:

1.* and ** denotes rejection of null at 5% and 1% significance levels.
2. Sample: 10 cross-sections, period 1994-2002
3. Regression equation contains individual effects, constant and time trend
4. Probabilities for Fisher tests are computed using asymptotic chi-square distribution. The other tests assume asymptotic normality
5. Eviews 5 econometrics software used

5.10 DIAGNOSTIC TESTS OF FIRST-ORDER ASYMPTOTIC THEORY ESTIMATION RESULTS

Equation 5.8 is estimated using GLM procedure in SAS statistical software and the results are presented in Table 5.6. In view of the fact that these results form the basis of bootstrapping, a number of diagnostic tests were performed. These include test of equality of variance and detection of influential observations.

5.10.1 Test of equality of residual variance across service sectors

The test of equality of variances is done using Levene's test (Levene 1960). Levene's test checks whether the variances of two or more populations are equal.

The null hypothesis is as follows;

$H_0 : \sigma_1 = \sigma_2 = ... = \sigma_{10}$ i.e. the standard deviations of the residuals from the ten different service sectors are equal.

$H_1 : \sigma_i \neq \sigma_j$ for at least one pair(i,j)

Given the residual e with sample size of N divided into k subgroups, where N_i is the sample size of the ith subgroup, the Levene's test is defined as;

$$W = \frac{(N-k)}{(k-1)} \frac{\sum_{i=1}^{k} N_i \left(\overline{Z}_{ij} - \overline{Z}\right)^2}{\sum_{j=1}^{k} \left(\overline{Z}_{ij} - \overline{Z}\right)^2} \tag{5.30}$$

$Z_{ij} = \left| e_{ij} - \overline{e} \right|$

Where $\bar{e}$ is the mean of the ith service sector. $\overline{Z}_{ij}$ are the group means of the Z_{ij} and Z is the overall mean of Z_{ij}. In this case N=90, k=10 and $N_i = 9$. The results are presented in Table 5.5.

Table 5.5: Tests of equality of residual variances

Service sector	Mean	Standard deviation
Airfreight	6.957398e-14	0.69441000
Education and training	4.322468e-14	1.38869791
Financial services	5.034553e-14	0.73569849
Legal services	4.706420e-14	0.85443271
Management consulting and public relations services	3.862959e-14	0.74640308
Ocean freight services	8.091059e-14	2.53313427
Ocean port services	-2.13656e-14	3.44243172
Research development and testing services	6.291264e-14	0.95871912
Telecommunications	6.906821e-14	1.43027313
Travel (tourism services	5.018208e-14	1.38965465
Levene's F -test statistic	2.54(0.013)	

Source: SAS statistical software output

Notes: Type I error probability in brackets.

The Levene's test shows that the variances of the residuals from the different service sectors are statistically different (i.e. there is heteroscedasticity).

5.10.2 Diagnostics for influential data observations

Influential observations are those whose presence in the data can have distorting effect on the parameter estimates and possibly the entire analysis. Outliers are data points that contain unusual dependent values (Mukherjee, White and Wuyts, 1998).

5.10.2.1 Leverage: The Hat-values

The hat-value (h_{ii}) measures the leverage of the regression. These values are so named because it is possible to express the fitted values $\hat{Y}_j$ (Y-hat) in terms of the observed values Y_i. The leverage is specified as follows;

$$h_{ii} = x_i \left(X'X \right)^{-1} x_i \tag{5.31}$$

The average value of h_{ii} should be k/n where k is the number of parameters and n is the number of observations. The standard criterion is to consider any data point for which $h_{ii} > {2k}/{n}$ a high leverage. In this study, the cut off is 0.8 (i.e. ${2 \times 36}/{90}$). On the basis of this, the data point 1994 for financial services is influential (Table A.17). This implies that if this point is moved up or down, the regression surface will tend to follow it.

5.10.2.2 Dffits statistic

The Dffits statistic is a scaled measure of the change in the predicted value for the *i*th observation. It is calculated as follows;

$$DFFITS_i = \frac{\hat{y}_i - \hat{y}_{i(i)}}{s_{(i)} \sqrt{h_{ii}}} \tag{5.32}$$

Where $\hat{y}_{i(i)}$ is the *i*th value predicted without using the *i*th observation. $s_{(i)}$ is the standard error with the ith observation deleted. Large absolute values of Dffits indicate influential observations. The rule of thumb is that if DFFITS is greater than 1 in the case of small data sets, or $2\sqrt{\frac{k}{n}}$ for large data, then the data point is influential. In this study the cut off is 1.26. The results in Table A.18 in the appendix show that the following data points are influential; ocean freight (1994, 1995); ocean port services (1995, 2000, 2001 and 2002); research development and testing services (1995); telecommunications (1996) and travel (2001). These observations have very high residual values and leverage.

5.10.2.3 CookD statistic

The CookD statistic is an overall measure of the influence of the ith observation on all the parameter estimates. In other words, it measures the change in the parameter estimates caused by deleting each observation.

$$D_i = \frac{(\hat{\beta} - \hat{\beta}'_{(i)})(X'X)(\hat{\beta} - \hat{\beta}_{(i)})}{ks^2} \sim F_{(k,n-k)} \tag{5.33}$$

Where $\hat{\beta}_{(i)}$ is the vector of parameter estimates after deleting the ith observation. Observations whose CookD statistic is greater than 10 per cent point of the F distribution are influential while observations with CookD statistics more than 50 per cent of F distribution are highly influential. At the 95 per cent confidence interval the F-statistic is 1.65. The results in Tables A.17 and A.18 show that none of the observation is influential on the parameter estimates.

5.10.2.4 Covratio statistic

This measures the effect of observations on the covariance matrix of the parameter estimates. It is computed as follows;

$$C_i = \frac{\left| s_{(i)}{}^2 (X'_{(i)} X_{(i)})^{-1} \right|}{\left| s^2 (X'X)^{-1} \right|} \tag{5.34}$$

Where $X_{(i)}$ is the X matrix without the ith observation. A value near 1 indicates that the observation has little effect on the precision of the estimates. The cut-off criterion is; $\left(C_i - 1\right) > \frac{3k}{n}$. In this study k=36, n=90. Therefore the cut off criterion is 1.2.

The results in Tables A.17 and A.18 in the appendix show that most of the regressors are influential on the precision of the estimates.

5.10.2.5 The fate of influential data observations

The problematic data points were investigated and found that the influential observations are not due to flaws in data. Thus the influential data points were retained since they inform the bootstrapping process. Firstly, the covratio statistic shows that pairs resampling cannot be used because regressors are not interchangeable as they affect the precision of the estimates. Secondly, the DFFITS and leverage statistics show that pooling of residuals from different sectors in the residual resampling process may not be appropriate. Instead, stratified resampling or wild bootstrap should be used.

5.11 IMPLEMENATION OF THE BOOTSTRAP METHOD

Two approaches to weighted error resampling are used to deal with the problem of heteroscedasticity and potential bias emanating from endogeneity of the regressors. The first approach, explained in Davison and Hinkley (1998: 270), assumes that the non-constant variance is known and this is build into the resampling procedure. In this approach, it is assumed that the residual variance is the true unknown variance. The second approach is the Liu-Davidson-Flachaire wild bootstrap, which is a more sophisticated method of estimating variances from individual residuals.

Two bootstrap macros in SAS statistical software were written to execute the bootstrap algorithms. The SAS bootstrap macro uses data step (i.e. procedures or *procs*) to execute standard procedures such as GLM and interactive matrix language (IML) for more complex algorithms such as resampling.

5.11.1 Algorithm for residual variance equals population variance by assumption

Firstly, Equation 5.8 is estimated using GLM procedure in SAS and residuals, v_{it}, generated. Secondly, the residuals are transformed through a standardization procedure involving subtracting the mean and dividing by sector variance as shown in Equation 5.35.

$$v_{it}^{s} = \frac{v_{it} - \bar{v}_i}{\hat{\sigma}_i} \qquad (5.35)$$

Where $\hat{\sigma}_i$ and $\bar{v}_i$ are the standard error and the mean of the residuals for specific service sector, respectively. The assumption is that the standardization in Equation 5.35 makes the residuals exchangeable and thus poolable.

Thirdly, resampling with replacement is done for the residuals in Equation 5.35 to generate v_{it}^* [25]. Fourthly, a bootstrap vector of response variable, $(y_{it}^*)_b$, is generated by adding the resampled vector of residuals multiplied by the variance for that sector to the vector of fitted response as follows;

$$(y_{it}^*)_b = \hat{y}_{it} + v^*{}_{it}\hat{\sigma}_i \tag{5.36}$$

Fifthly, these bootstrapped response variables are then regressed using GLM on the fixed explanatory variables to estimate a bootstrapped vector of coefficients, $\hat{\beta}_b^*$, as in Equation 5.37;

$$(y_{it}^*)_b = \hat{\beta}_b^{*\prime} z_{it} + \eta_{it} \tag{5.37}$$

Sixthly, this procedure from the first to the fifth is repeated B times (in this case, B=3000). The bootstrapped regression coefficients for each resample are placed in a (3000×36) matrix. Each column in this matrix is converted into an estimate of the sampling distribution of the $\hat{\beta}$ by placing a probability of $1/3000$ on each value of $\hat{\beta}_b^*$.

Seventhly, the bias of the estimated coefficients is computed using Equation 5.26. This step does not only determine whether endogeneity is a serious problem but it also informs the decision of which method in Section 5.8.5 to use in constructing confidence intervals.

[25] Stratified resampling is not used because there is not much variability within the service sector on account of the short time dimension 1994-2002.

Eighthly, confidence intervals are constructed using the percentile method. This entails sorting the bootstrap parameters in ascending order and then selecting the appropriate percentiles. For instance, with 3000 replications and using the 95 per cent confidence interval, the bootstrapped parameter number 75 is selected as the lower confidence limit value and number 2925 as the upper confidence limit value in the empirical distribution function (EDF). Hypothesis tests can then be performed.

5.11.2 Liu-Davidson-Flachaire wild bootstrap algorithm

The first step is the same as the previous algorithm but the second step entails transforming the residuals using the second form of Mackinnon and White (1985) HCCME in Equation 5.22 is used to transform the residuals;

$$a_{it}v_{it} = \left(\frac{1}{\sqrt{1-h_{it}}}\right)v_{it} \tag{5.38}$$

This adjustment compensates for the fact that the OLS residuals (and thus GLM) tend to understate the true errors.

In the third step, since the SAS software does not have a customised Rademacher distribution in Equation 5.25, this was done manually. This entailed generating a series, which is a sequence that alternate between 1 and –1. Since there are 90 observations in total, there were 45 observations with 1 and 45 observations with –1 effectively constructing a Rademacher distribution in Equation 5.25.

Fourthly, resampling with replacement is done for the generated variable that follows the Rademacher distribution. As pointed out in Liu (1988), this lattice distribution satisfies three requirements;

$$E(t_{it}) = 0, E(t_{it}^2) = 1 \text{ and } E(t_{it}^3) = 1 \tag{5.39}$$

The first condition shows that the Rademacher distribution centres the bootstrap statistic around zero. The second condition states that the Rademacher distribution centres the variance around 1 while the last condition corrects for skewness in the Edgeworth expansion of the sampling distribution of the parameter estimates.

Fifthly, this is multiplied with the modified residuals in Equation 5.38 as follows;

$$v_{it}^{*} = a_{it} e_{it} t_{it} \tag{5.40}$$

The rest of the steps are the same as the previous approach in Section 5.11.1. It is imperative to note that since the macros use the computer clock as the seed, one may not get exactly the same results unless the program is re-run at exactly the same time. Table 5.6 presents first-order asymptotic theory results while Tables 5.7 and 5.8 present the two bootstrap versions.

The overall explanatory power of the model (in terms of adjusted R^2) shows that the regressors explain about 50 per cent of the variation in log odds of IIT. The F-statistic shows that the regressors are jointly significant in explaining the dependent variable. The Durbin h statistic shows that the model does not suffer from serial correlation problem.

The fourth column in the bootstrap results (Tables 5.7 and 5.8) presents the standardised bias and shows that the estimates in Equation 5.8 are unbiased and therefore endogeneity in the dynamic panel model is not a serious problem.

One other diagnostic test is the fact that the model should predict IIT within the 0 and 1 range. This requirement is tested by using the relationship;

$$\ln\left(\frac{II\hat{T}}{1 - II\hat{T}}\right) = pred \tag{5.41}$$

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Where $II\hat{T}$ is the predicted IIT index and *pred* is the predicted log odds ratio of IIT and 1-IIT. This can be rewritten as;

$$II\hat{T} = \frac{1}{1+e^{-\Pr ed}} \tag{5.42}$$

Figure 5.1 shows the EDF for the predicted IIT in financial services. A normal distribution line is superimposed to see how the EDF approximates the latter. IIT=0 and IIT=1 are the lower and upper bounds of the GL IIT index. The figure shows that the model predicts IIT within the 0 and 1 range. The EDF for IIT in other services also meet the same criterion (Figure A.1 through Figure A.9 in the appendix). Although the thesis follows a classical approach to probability interpretation as opposed to Bayesian view, the EDFs can provide an approximation of the underlying distribution that generates South Africa-US IIT in the selected unaffiliated services. In other words, a subjective probability interpretation is used. This is not strictly Bayesian since neither prior information regarding the underlying distribution F nor population parameters generated from joint posterior densities as explained in Davison and Hinkley (1998:512-514).

Hypothesis testing in bootstrap is done by checking whether $\beta = 0$ is contained in the confidence interval of the bootstrap results. For example for the case of the difference in market size, the bootstrap confidence intervals do not contain the element zero implying that it is statistically significant. This can be seen in Figure 5.2, which shows the EDF of this coefficient with its 99 per cent bootstrap confidence intervals. This conclusion also agrees with the first-order asymptotic results in Table 5.6.

The LCL and UCL refer to 99 per cent lower and upper confidence intervals, respectively. Since $\beta = 0$ is not contained in the interval, the difference in market size is statistically different from zero. The same can be done for all the other coefficients.

Table 5.6: First-order asymptotic theory panel data estimation results

	First-order asymptotic theory results		
Independent variables and service sector	**Estimate**	**Std error**	**p-value**
Intercept	73.496***	19.278	0.000
y_{it-1}	-0.385***	0.078	0.000
Difference in per capita income	-126.738**	42.887	0.004
Difference in market size	-16.428**	6.528	0.015
US foreign direct investment in SA	29.593**	14.562	0.047
Nominal exchange rate (Rand/$)	67.154*	36.059	0.068
Openness to services trade in SA	-6.679	4.999	0.187
Openness to services trade in the US	-1.128	3.644	0.758
Deregulation in South Africa:			
Air freight services	-2.063	1.425	0.154
Education and training services	2.322*	1.376	0.097
Financial services	1.505	1.376	0.279
Legal services	-0.391	2.984	0.896
Management, consulting and public relation services	4.337*	2.288	0.063
Ocean freight services	-4.647**	1.425	0.002
Ocean port services	8.802**	2.447	0.001
Research development and testing services	3.153	2.513	0.215
Telecommunications services	-8.474**	3.356	0.015
Travel (tourism) services	1.287	1.415	0.367
Service-specific fixed effects:			
Air freight services	24.214*	8.685	0.007
Education and training services	-11.549	8.383	0.174
Financial services	-3.949	9.046	0.664
Legal services	-6.708	14.712	0.650
Management, consulting and public relation services	-22.740*	12.295	0.070
Ocean freight services	40.920***	8.558	0.000
Ocean port services	-56.507***	14.388	0.000
Research development and testing services	-15.230	17.654	0.392
Telecommunication services	54.305**	17.818	0.004
Travel (tourism) services[a]	-2.756		
Time-specific effects:			
1994	-4.383**	1.777	0.017
1995	-2.152	2.560	0.404
1996	-8.805**	3.590	0.017
1997	-0.866	1.514	0.570
1998	-4.648**	2.085	0.030
1999	4.314*	2.316	0.068
2000	6.114**	2.070	0.005
2001	4.731 **	2.098	0.028
2002[a]	5.695		
Diagnostic statistics			
Rsquare	0.684095		
Adjusted R-square	0.502806		
F-statistic	3.50(0.000)		
Durbin-h	1.0008		
First order autocorrelation coefficient	-0.0707		

Notes: Sample period: 1994-2002

[a]The effects of travel service-effects are estimated as minus the sum of other service effects. The same applies to the time specific effects of 2002.

*, **, and *** implies significance at 10 per cent, 5 per cent and 1 per cent, respectively.

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Table 5.7: Pooled residual bootstrap results

	Bootstrap (3000 replications)				
Independent variables and service sector	**Estimate**	**Std error**	**Bias**	**Confidence (percentile method)**	
				Interval	**%**
Intercept	71.698***	19.146	0.093	21.215, 115.085	99
y_{it-1}	-0.389***	0.087	0.046	-0.638, -0.155	99
Difference in per capita income	-122.282***	44.613	-0.099	-221.076, -7.170	99
Difference in market size	-16.563***	5.591	0.024	-28.648, -3.434	99
US foreign direct investment in SA	29.639***	11.928	-0.004	2.483, 60.835	99
Nominal exchange rate (Rand/$)	63.045	43.624	0.094	-7.196, 138.793	90
Openness to services trade in SA	-6.574**	3.413	-0.031	-12.326, -0.358	95
Openness to services trade in the US	-1.166	1.592	0.024	-3.809, 1.364	90
Deregulation in South Africa:					
Air freight services	-2.086***	0.691	0.033	-3.993, -0.167	99
Education and training services	2.347**	0.963	-0.026	0.417, 4.156	95
Financial services	1.492**	0.805	0.016	0.057, 3.178	95
Legal services	-0.415	1.664	0.014	-3.153, 2.365	90
Management, consulting and public relation services	4.353***	1.268	-0.013	1.023, 7.462	99
Ocean freight services	-4.687***	1.455	0.027	-7.934, -1.425	99
Ocean port services	8.756***	2.985	0.015	1.427, 15.084	99
Research development and testing services	3.104*	1.848	0.027	0.009, 6.007	90
Telecommunications services	-8.409***	2.409	-0.031	-15.366, -2.893	99
Travel (tourism) services	1.269	0.945	0.019	-0.219, 2.801	90
Service-specific fixed effects:					
Air freight services	24.301***	5.032	-0.017	12.253, 36.677	99
Education and training services	-11.849*	6.102	0.049	-22.769, -1.568	90
Financial services	-3.856	6.054	-0.015	-13.650, 6.094	90
Legal services	-6.753	9.126	0.005	-23.087, 8.722	90
Management, consulting and public relation services	-22.910***	6.890	0.025	-40.325, -4.224	99
Ocean freight services	41.109***	9.102	-0.021	17.456, 61.606	99
Ocean port services	-56.255***	18.193	-0.014	-97.319, -8.288	99
Research development and testing services	-14.837	13.177	-0.030	-36.994, 6.377	90
Telecommunication services	53.816***	13.233	0.037	24.155, 89.478	99
Travel (tourism) services[a]	-2.766				
Time-specific effects:					
1994	-4.296**	2.025	-0.043	-7.775, -0.204	95
1995	-2.242	3.299	0.027	-7.454, 3.424	90
1996	-8.443**	4.071	-0.089	-16.370, -0.826	95
1997	-0.976	1.893	0.058	-4.009, 2.124	90
1998	-4.410*	2.477	-0.096	-8.409, -0.446	90
1999	4.058	2.586	0.099	-0.399, 8.454	90
2000	5.893**	2.340	0.094	1.362, 10.377	95
2001	4.785*	2.662	-0.020	0.253, 8.983	90
2002[a]	5.631				

Notes: Sample period: 1994-2002

[a]The effects of travel service-effects are estimated as minus the sum of other service effects. The same applies to the time specific effects of 2002.

*, **, and *** implies significance at 10 per cent, 5 per cent and 1 per cent, respectively.

Table 5.8: Liu-Davidson-Flachaire wild bootstrap results

Independent variables and service sector	Bootstrap (3000 Replications) Estimate	Std error	Bias	Confidence (percentile method) Interval	%
Intercept	74.744***	19.039	-0.066	31.579, 124.273	99
y_{it-1}	-0.386***	0.148	0.007	-0.729, -0.062	99
Difference in per capita income	-129.108***	40.751	0.058	-220.852, -41.813	99
Difference in market size	-16.678***	4.915	0.051	-29.183, -4.332	99
US foreign direct investment in SA	29.455*	18.239	0.008	1.284, 58.098	90
Nominal exchange rate (Rand/$)	68.606**	34.245	-0.042	3.721, 134.201	95
Openness to services trade in SA	-6.627	4.345	-0.012	-13.323, 0.308	90
Openness to services trade in the US	-1.051	1.644	-0.047	-3.909, 1.730	90
Deregulation in South Africa:					
Air freight services	-2.077*	1.159	0.012	-4.026, -0.205	90
Education and training services	2.189**	1.187	0.112	0.024, 4.521	95
Financial services	1.466	1.053	0.037	-0.285, 3.167	90
Legal services	-0.324	2.310	-0.029	-4.020, 3.344	90
Management, consulting and public relation services	4.351***	2.060	-0.007	0.130, 9.301	99
Ocean freight services	-4.693***	1.899	0.024	-9.446, -0.547	99
Ocean port services	8.839**	4.065	-0.009	1.146, 16.462	95
Research development and testing services	3.24**	1.644	-0.053	0.115, 6.483	95
Telecommunications services	-8.484***	2.248	0.004	-13.927, -3.288	99
Travel (tourism) services	1.249	1.057	0.036	-0.589, 2.937	90
Service-specific fixed effects:					
Air freight services	24.280***	8.084	-0.008	5.631, 44.193	99
Education and training services	-10.676*	6.129	-0.142	-20.955, -0.994	90
Financial services	-3.654	5.839	-0.050	-12.887, 6.452	90
Legal services	-7.167*	12.795	0.036	-28.433, -1.352	90
Management, consulting and public relation services	-22.878***	10.180	0.014	-46.733, -1.352	99
Ocean freight services	41.231***	15.010	-0.021	9.363, 73.926	99
Ocean port services	-56.715***	24.558	0.008	-114.372, -0.412	99
Research development and testing services	-16.014	10.447	0.075	-33.909, 1.438	90
Telecommunication services	54.232***	12.095	0.006	24.689, 83.467	99
Travel (tourism) services[a]	-2.639				
Time-specific effects:					
1994	-4.495***	1.419	0.079	-8.569, -1.387	99
1995	-2.224	2.274	0.032	-5.991, 1.739	90
1996	-9.005***	3.474	0.058	-16.993, -1.806	99
1997	-0.803	1.353	-0.047	-3.056, 1.224	90
1998	-4.733**	2.090	0.041	-8.626, -0.466	95
1999	4.437**	2.238	-0.055	0.128, 8.618	95
2000	6.242***	2.081	-0.062	1.542, 11.419	99
2001	4.771***	1.643	-0.024	0.968, 8.690	99
2002[a]	5.81				

Notes: Sample period: 1994-2002

[a]The effects of travel service-effects are estimated as minus the sum of other service effects. The same applies to the time specific effects of 2002.

*, **, and *** implies significance at 10 per cent, 5 per cent and 1 per cent, respectively.

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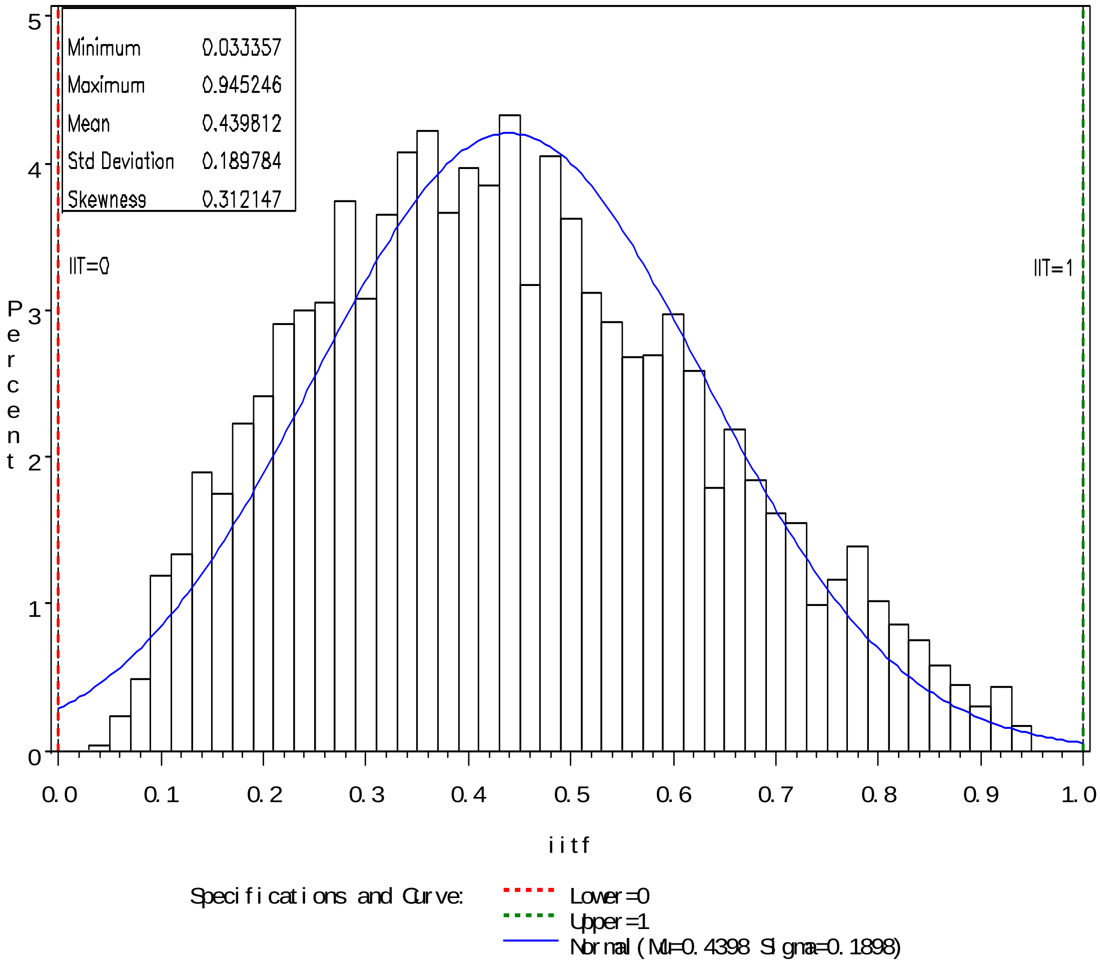
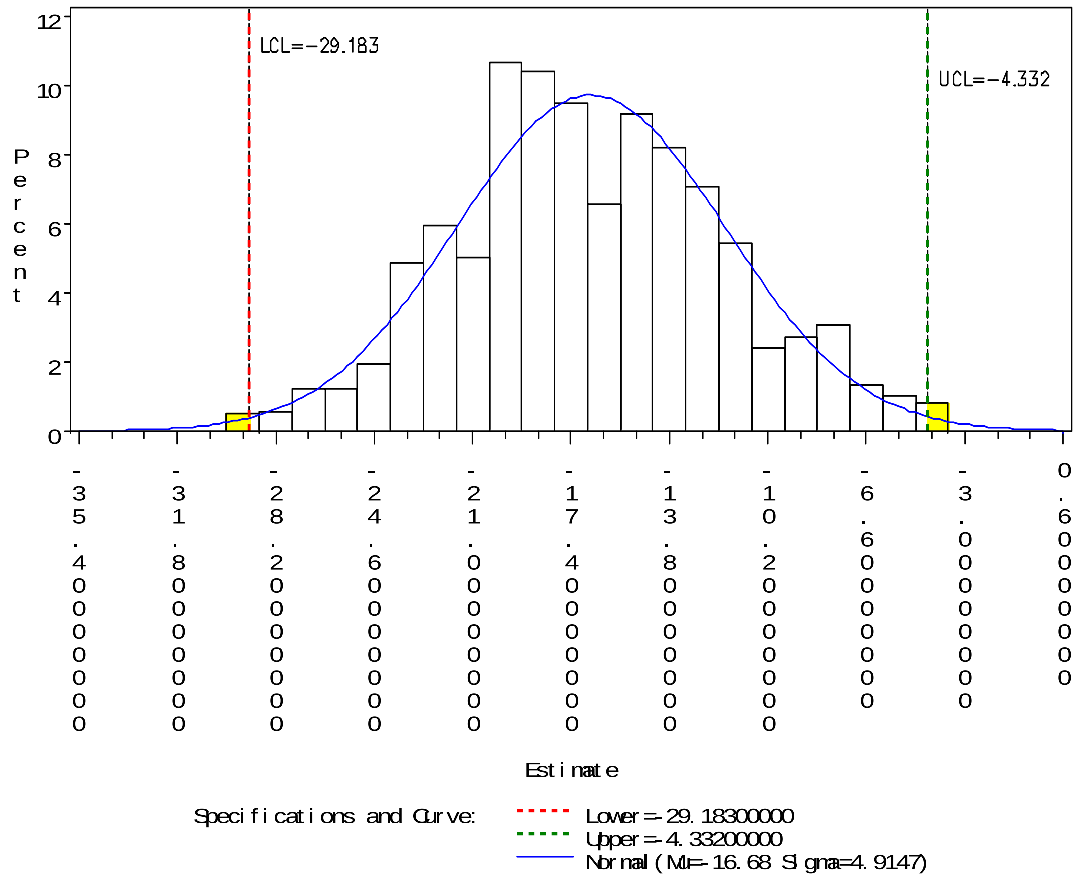
Figure 5.1: EDF of the predicted IIT in financial services



Source: SAS statistical software output from Liu-Davidson-Flachaire wild bootstrap algorithm

Figure 5.2: EDF of the coefficient for the difference in market size between South Africa and the US (99 per cent confidence interval)



Source: SAS statistical software output from Liu-Davidson-Flachaire wild bootstrap algorithm

5.12 INTERPRETATION OF THE ESTIMATION RESULTS

Firstly, the intercept is interpreted as the global mean since effects coding is used in constructing fixed effects. The service-specific effects are deviations from this grand mean as opposed to regression coding, where the effects would be deviations from the reference class.

Secondly, using the classical statistical inference and the bootstrap approaches, the coefficient for the lagged dependent variable (y_{it-1}) is negative and statistically significant. The fact that there is a positive bias in the two bootstrap methods (column 4 in Tables 5.7 and 5.8) confirms the theoretical postulation of Nickell (l981) that if the population parameter is negative, then the bias is positive and vice versa.

Thirdly, differences in demand structure, proxied by differential in capita income, has a negative sign as anticipated and is statistically significant at 1 per cent level. This is in line with the Chamberlin-Heckscher-Ohlin (CHO) model of horizontally differentiated IIT (HIIT) and agrees with many "North-South" studies on IIT in goods presented in Table 10.1 of Greenaway and Milner (2002: 184). The results are similar to those in Li *et al.,* (2003, 2005). However, the results are inconsistent with vertically differentiated IIT (VIIT) theoretical model of Flam and Helpman (1987) and the empirical findings by Stanley and Clark (1999) dealing with goods and Lee and Lloyd (2002) study on services. These studies postulate a positive relationship between per capita income and IIT. Additionally, despite this study's inability to disentangle HIIT from VIIT, the consistency with CHO model remotely suggests that the former dominates South Africa-US IIT in services.

Fourthly, the classical and the two bootstrap approaches show that the difference in market size is negatively related to odds ratio of IIT. The difference in market size represents differences in the existence of economies of scale and the different ability of South Africa and US to provide differentiated services. The results agree with both models of "love-of-variety"(Krugman, 1979) or "the ideal-variety" (Lancaster, 1980), which suggest that larger markets have the potential to allow for greater differentiation in services. The results are also consistent with the finding in Li *et al.,* (2003, 2005).

Fifthly, the coefficient for US FDI in South Africa has a positive relationship with log odds of unaffiliated IIT in services. The positive relationship is consistent with the theoretical trade models of Helpman and Krugman (1985) and Markusen and Venables (1998, 2000). This means that presence of US multinationals complement rather than substitute exports of services by South African firms. The finding agrees with the results in Li *et al.,* (2003, 2005). This is however, inconsistent with the original hypothesis that US FDI in South Africa should substitute South Africa-US IIT in unaffiliated services. The results show that US MNC overcome the costs of trade barriers in services (highlighted in Chapter 4) by establishing themselves in South Africa (host country) and then generate arms-length trade with the US (home country).

Sixthly, the classical and the two bootstrap results conflict when it comes to the coefficient for the change in nominal exchange rate. The first-order asymptotic theory approach shows that the coefficient is positive and statistical significant at 10 per cent level. Although the wild bootstrap supports this conclusion albeit at 5 per cent level, the other bootstrap approach suggests that nominal exchange rate does not affect the odds ratio of IIT. Given this conflict, the thesis concludes that the rand-dollar nominal exchange rate has limited positive effect on the odds ratio of IIT. This implies that although a depreciation of the rand makes South Africa's exports competitive and imports dearer, such effect is not statistically significant.

Seventhly, the coefficients for trade openness to all the four modes of supply in South Africa and the US are inimical to IIT in services. However, the classical and wild bootstrap shows that the coefficient is not statistically significant. In terms of the sign, the results are in line with Falvey's (1981) model of VIIT, which demonstrates that countries with lower tariff barriers have higher levels of IIT. The results are contrary to the study by Lee and Lloyd (2002: 170) who find a positive and insignificant relationship. The difference in the finding with Lee and Lloyd (2002) may emanate from the method used to define a proxy for trade orientation. Their trade orientation is proxied by residuals from a regression of the log of per capita services trade on the log of per capita income and log of population. The thesis uses the Hoekman (1995) trade barriers indices constructed using GATS schedules (Chapter 4) and suffers from the following measurement errors. Firstly, the openness indices only cover the period 1994-1998. Secondly, the indices are not adjusted to take into consideration the uniqueness of mode 2 supply.

Eighthly, the coefficient for the degree of deregulation in South Africa has the expected sign in most services except airfreight; legal services; ocean freight and telecommunication services. However, in terms of statistical significance, the relationship is strong in airfreight; educational and training services; management and consulting services; ocean freight; ocean port services; research development and testing services and telecommunication. This finding is in line with the results in *Li et al.* (2003).

Ninthly, the service-specific effects are deviations from global mean. Using the wild bootstrap, the value of 24.30 for airfreight means that the air freight-specific effects cause the odds ratio of IIT in this sector to be above the grand mean of 74.744 by 24.30 units. The coefficient for the travel services is calculated as minus the sum of the other effects. This emanates from the effects coding approach where this class is coded –1 instead of 0 in regression coding approach. The service-specific effects are positive in airfreight; ocean freight and telecommunication services. This means that there are time-invariant service-specific characteristics which bolter South Africa-US IIT in the service sectors. On the other hand there are negative service-specific effects in education services; financial services; legal services; management, consulting and public relations; ocean port services; research development and testing services and travel. This means that there are time-invariant unique characteristics in these services that tend to discourage South Africa’s exports and instead promote imports of services from the US and should be identified using sector-specific surveys.

The time-specific effects are also interpreted with reference to the grand mean (intercept). The time-specific effects pick up the effects of any variables affecting South Africa-US IIT in selected services that vary over time, are constant across sectors (sector-invariant) and have not been included in the list of explanatory variables. The coefficients for the period 1994-1998 are negative but positive thereafter. However, in terms of statistical significance, the two bootstrap approaches show that the coefficients for the period 1994, 1996, 1998, 2000, and 2001 are significant. This pattern confirms the fact that following

South Africa's new political dispensation in 1994, there was a high affinity for imports of services from the US and this changed from 1999 onwards.

5.13 POLICY IMPLICATIONS

Firstly, some policy implications do emerge from the negative relationship. The CHO monopolistic competition trade model argues that regional integration and trade liberalisation involving trade between relatively similar economies would bolster disproportionately intra-industry specialisation and trade in horizontally differentiated products (Greenaway and Milner 2002: 192). Applying this to services, there are two policy options for South Africa.

On one hand, South Africa could use the policy implications of CHO, described in Greenaway and Milner 2002: 192, in arguing that since there is dissimilarity in demand with the US, such trade does not satisfy industrialisation aims (technology transfer, greater economies of scale etc.) and would involve higher factor adjustment costs in terms of job losses[26]. This would suggest that South Africa should view the services component of the SACU-US FTA with caution and in fact use trade and industrial policy strategically to fashion the location of production in Southern Africa in the hope of deriving future scale advantages in services. Following this line of argument, South Africa should promote narrower regional integration and trade liberalisation involving trade between close and economically similar economies like those in NEPAD, where IIT is likely to be higher.

On the other hand, there are other factors, which militate against this kind of approach. The CHO story precludes the role of globalisation and the GATS initiatives, which will eventually make consumer preferences for services converge between the US and South Africa (Salvatore, 2004b: 544). Additionally, the CHO does not deal with vertically (quality) differentiated services based on the model of Flam and Helpman (1987), which

[26] In other words, most firms supplying services would be located in the US to supply services in South Africa.

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has been found to be the main type of IIT in goods between the US and developing countries (Stanley and Clark, 1999, Kunin and Zigic, 2003). In this regard broader regional groupings are desirable (Greenaway and Milner, 2002:193). This supports the SACU-US FTA.

Secondly, the finding that limited market size in service sectors constrains innovation and production of differentiated services calls for a need to expand the market size for services sector in South Africa so that firms can reap economies of scale.

Thirdly, the finding that US MNCs overcome the costs of trade barriers in services (highlighted in Chapter 4) by establishing themselves in South Africa (host country) and then generate arms-length trade with the US (home country) calls for initiatives in South Africa to promote FDI from the US.

Fourthly, there is need for sector-specific surveys to identify unique characteristics in services with negative service-specific effects (education and training; financial services; legal services; management, consulting and public relation services; ocean port services; research development and testing services and travel services). These characteristics tend to discourage South Africa's exports and instead promote imports of services from the US.

5.14 MAIN INSIGHTS AND CONCLUDING REMARKS

The aim of this chapter is to expand the existing literature and, for the first time, test whether South Africa-US IIT in selected services is caused by the same factors in the studies of manufacturing industries. Based on modern trade theories, a number of hypotheses are specified as the major determinants of unaffiliated IIT in the selected services. Dynamic panel data techniques within a GLM framework are used to model log odds of IIT. However, hypothesis tests are performed using bootstrapping techniques that are robust to heteroscedasticity. The bootstrap approach showed that the dynamic panel data estimates are unbiased and the model forecasts IIT within the 0 and 1 range.

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The empirical results show that, in principle, South Africa-US IIT in services is determined by factors similar to those in other "North-South" IIT studies (such as Clark and Stanley, 1999). Specifically, IIT is determined by differences in per capita income, US foreign direct investment in South Africa, degree of economic freedom in South Africa, and service-specific and time-specific effects. The results also show that HIIT dominates VIIT in South Africa-US IIT in services.

A number of policy implications are also drawn from the study. Firstly, South Africa should view the services component of the SACU-US FTA with caution and in fact should use trade and industrial policy strategically to fashion the location of production in Southern Africa in the hope of deriving future scale advantages in services. Indeed, South Africa should promote narrower regional integration and trade liberalisation involving trade between close and economically similar economies.

Secondly, there is need to expand the market size for services sector in South Africa so that exporters can reap economies of scale. This can be done through programs that increase the purchasing power of South Africans as well as regional economic integration like SACU.

Thirdly, there is a positive relationship between FDI and IIT implying that US multinationals in South Africa play a complementary role rather than displacing exports by South Africans. This calls for the need to promote investment from the US to facilitate service exports.

Fourthly, there is need for sector-specific surveys to identify unique characteristics in services with negative service-specific effects (education and training; financial services; legal services; management, consulting and public relation services; ocean port services; research development and testing services and travel services). These characteristics tend to discourage South Africa's exports and instead promote imports of services from the US.

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Having looked at the causes of South Africa-US IIT in services, the next chapter focuses on the consequences of this trade on labour market adjustment costs in terms of job losses.