Comparison Study of Methodologies for Estimating the Long-run Exchange Rate Pass-Through to Import Prices for South Africa

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DECLARATION

I declare that this research report is my own, unaided work. It is being submitted for the Degree of Master of Science to the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination to any other University.

(Signature)

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Abstract

The resilience of trade balances of the major industrialised economies such as the US and Japan to changes in their exchange rates following the switch from fixed to floating exchange rate regimes, triggered interest in the exchange rate pass-through relationship. Because of the importance of the pass-through issue particularly in economic policy formulation, a sizeable literature has developed over recent years. Comprehensive surveys of this literature include Menon (1995), Goldberg and Knetter (1997) and McCarthy (2002). However, not much attention has been paid to the comparison of the methodologies for estimating exchange rate pass-through. This research report aims to address this imbalance by comparing some of the exchange rate pass-through estimation methodologies via a Monte Carlo simulation study, based on the South African data set. The econometric results reported in this research report suggest that the Johansen type VECMs are superior to polynomial distributed lag models, exchange rate pass-through to South Africa's import prices is incomplete (around 78%) and that the speed of adjustment to long-run equilibrium is low, about 7 per cent of disequilibrium in the previous month is corrected in the current month. We conclude that if we are not sure about the unit root properties of the data (as is normally the case), then the ARDL precedure is the appropriate model for empirical work.

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To my dear departed mom and grand mom; my dad, brothers and my sister.

Chapter 1

Background Theory of Exchange Rate Pass-through

1.1 Introduction

The breakdown of the Bretton Woods system of international monetary management, which provided for fixed exchange rates, paved the way for the advent of floating exchange rates. This switch was initially greeted with high expectations, mainly because of the claim that it would provide for a better system of international adjustment. However the floating exchange rates regime brought with itself a considerable amount of variability to the world's foreign exchange markets. Surprisingly, trade balances (the difference between the monetary value of exports and imports in an economy over a certain period of time) of major trading nations like the United States and Japan maintained remarkable resilience to such variations (Menon, 1995). This prompted research to account for this 'adjustment puzzle', and has seen many authors examining the underlying relationships between exchange rates and prices of internationally traded goods, now popularly known as exchange rate pass-through relationships (Menon, 1995). It is defined as the degree to which import prices respond to changes in exchange rates (Campa and Minguez, 2006).

The reflection of exchange rate fluctuations and the rate at which that happens in import prices, and ultimately in increased domestic consumer price inflation, remains a huge topic in time series econometric research (Rangasamy and Farrell, 2002). In this research report, we focus on changes in the rand's exchange rate and link them to the domestic currency price of imports. This pass-through of exchange rate changes to import prices is the traditional focus of exchange rate pass-through studies surveyed in Menon (1995) and Goldberg and Knetter (1997).

The primary aim of this research report is to estimate the proportion of exchange rate changes that pass-through to South Africa's import prices in the long run. According to Barhoumi (2006), exchange rate pass-through studies into import prices were once based on a statistical relationship governed by the equation

$$\Delta LP_t = \beta_1 \Delta LE_t + \upsilon_t. \tag{1.1}$$

The series LP_t and LE_t are the natural logarithms of import price and nominal exchange rate respectively and Δ is the first difference operator. For the series LP_t, it is defined as $\Delta LP_t = LP_t - LP_{t-1}$. The extent to which exchange rate changes are passed through to import prices is measured by the value of β_1 and υ_t is the stochastic error term assumed to be distributed as $\upsilon_t \sim N(0, \sigma^2)$. This specification was criticized by Campa and Goldberg (2003), who argue that it only represents a non-structural statistical relationship with no economic interpretation. They advocate for the additional inclusion of controls to capture the costs to the exporter.

Traditionally however, pass-through of exchange rate changes to import prices is measured using an import price equation. A much simpler scenario arises when a country is small and is a price-taker on perfectly competitive world markets. Ignoring tariffs, transport costs and other distortions to trade, arbitrage (the opportunity to buy an asset at a low price and sell it immediately on a different market for a higher price) will ensure that the law of one price holds.

1.2 The law of one price

The law of one price (LOP) maintains that in an efficient market, identical products sell at the same price when expressed in a common currency in different destinations in the absence of transportation costs and differential taxes (Goldberg and Knetter, 1997). Let P_t denote domestic price of the imported good, P_t^* the world price of the corresponding good in the world currency, and E_t the exchange rate (quoted as the domestic currency price of the world currency). If the law of one price holds, then:

$$P_t = E_t P_t^*. \tag{1.2}$$

Assumptions of cost-less distortions to trade are unlikely to hold in practice, but studies of the LOP are themselves an area of research (Choi, Laibson and Madrian, 2006; Haskel and Wolf, 2001). Literature on exchange rate pass-through into import prices, according to Barhoumi (2006), includes pass-through into disaggregate import prices of specific domestic industries and pass-through into aggregate import prices. In this research report, we assume that the LOP holds and note that equation 1.2 provides the basis for an aggregate import price equation (ignoring aggregation issues). If we define P_t and P_t^* in terms of aggregate prices, a log transformation of equation 1.2 is given by

$$LP_t = LE_t + LP_t^* \tag{1.3}$$

where the world price, P_t^*, is made up of the exporters marginal cost, MC_t (change in total cost arising when the quantity produced changes by one unit) and the markup, $MKUP_t$ (increase in the price of goods to create a profit margin for a business) as:
$P_t^* = MC_t MKUP_t$. The log transformation of the world price equation is given by

$$LP_t^* = LMC_t + LMKUP_t. \tag{1.4}$$

Substituting for log world price into equation 1.3 gives

$$LP_t = LE_t + LMC_t + LMKUP_t. \tag{1.5}$$

According to De Bandt, Banerjee and Kozluk (2007), industrial organisation literature sheds light on why exchange rate changes affect import prices differently through markup determinants such as the competitive conditions exporters face in destination markets. Thus, the estimated elasticities of the exchange rate pass-through are determined by the:

(1) Effects of the direct unit translation of exchange rate movement.

(2) Markup response to offset the translation effect.

(3) Direct effects of exchange rate movements on marginal costs, in particular, sensitivity of prices of inputs to exchange rate fluctuations.

The market share of domestic producers relative to foreign producers determines how markup responds to the translation effect of exchange rate fluctuations. This is the form of competition existing in the market for the industry together with the level of price discrimination (charging a different price to different groups of customers for the same commodity or service for reasons independent of costs) (De Bandt *et al*, 2007).

Generally, pass-through is high if the destination country has a larger share of imports and /or imported inputs in its total industry or if the degree of price discrimination is high. On the other hand, exchange rate pass-through may be lower if exporters compete with domestic producers for the market share. This is because exporters may choose to absorb some of the exchange rate fluctuations within the markup rather than passing them through to the price in the importing country currency, called local currency pricing or pricing to market. This implies that industry markups can be assumed to include a component specific to the type of good (independent of the exchange rate) and a direct response to changes in exchange rate as follows

$$LMKUP_t = \beta_0 + \delta LE_t. \tag{1.6}$$

In the same way, marginal cost is a function of demand conditions, D_t, in the destination country, labour wages in the exporting country, W_t, and the foreign currency price of the commodity, FCP_t, as

$$LMC_t = \eta_0 LD_t + \eta_1 LW_t + \eta_2 LE_t + \eta_3 LFCP_t. \tag{1.7}$$

Upon substituting equation 1.6 and equation 1.7 into equation 1.5, we get

$$LP_t = \beta_0 + (1 + \delta + \eta_2)LE_t + \eta_0 LD_t + \eta_1 LW_t + \eta_3 LFCP_t + \upsilon_t \tag{1.8}$$

where υ_t is the stochastic error term added to account for error. In the Campa, Goldberg and Minguez (2005) 'integrated world market' specification, $\eta_0 LD_t + \eta_1 LW_t + \eta_3 LFCP_t$ is the opportunity cost of allocating the same goods to other customers. It is reflected in the world price P_t^*, expressed in the world currency to give the final equation:

$$LP_t = \beta_0 + \beta_1 LE_t + \beta_2 LP_t^* + \upsilon_t \tag{1.9}$$

where $\beta_1 = 1 + \delta + \eta_2$ is the elasticity of the exchange rate pass-through to aggregate import prices and β_2 is the pass-through coefficient from foreign price changes (Rangasamy and Farrell, 2002).

The literature on exchange rate pass-through can be divided into two main streams namely

(1) Exchange rate pass-through into import prices.

(2) Exchange rate pass-through into consumer prices.

Studies for exchange rate pass-through into consumer prices are relevant for monetary policy designs. This is so since the link between prices of internationally traded goods and exchange rates is the pass-through relationship. This research report however, focuses only on exchange rate pass-through into import prices. Recent work on this stream of the pass-through relationship include Barhoumi (2006) and Campa and Minguez (2006).

In general, a significant part of economic theory deals with long-run equilibrium relationships that are generated by market forces and behavioral rules. As a result, empirical time series econometric studies can be interpreted as attempts to evaluate such relationships in a dynamic framework (Dolado, Gonzalo and Marmol, 1999). Time series literature is found in a number of books and journals in different areas such as statistics, econometrics and engineering. The seminal work in statistics is Box and Jenkins (1970). On the other hand, econometric time series is based primarily on the work of Granger and Weiss (1983) and the seminal paper of Engle and Granger (1987).

1.3 Data

Because of the data availability restrictions, this study opted to use the nominal effective exchange rate of the rand (LE_t) as the exchange rate variable, the imported component of the PPI (LP_t) as the proxy for import prices, and an index of foreign wholesale price indices (LP_t^*), weighted on the same basis as the nominal effective exchange rate of the rand as the proxy for foreign prices. All data are at the monthly frequency, with the shorter data sample running from January 1980 to December 2001 and the longer sample extending to April 2007.

1.4 Organisation of the Research Report

The rest of the research report is organised as follows. Chapter 2 gives the definition of terms, operators and some well known time series processes. Possible methodologies for estimating exchange rate pass-through are then set out in Chapter 3, and Chapter 4 gives a review of the related literature. The implementation of the possible methodologies is the subject of Chapter 5 and the results of the study are presented and discussed in Chapter 6, while Chapter 7 concludes the work and makes recommendations for further study.

Chapter 2

Time Series Analysis Background

2.1 Time Series Definition

A time series is a sequence of observations ordered in time, made on a stochastic variable. It can be either continuous or discrete but we focus on the latter since prices are recorded on a monthly basis. Time series analysis assumes that data are generated according to some theoretical data generating process. We observe only one realisation of the stochastic process (a statistical phenomenon that evolves in time according to probabilistic laws) and we call this observed sample a finite sample from a doubly infinite sequence. If we denote our time series by Y_t, then the doubly infinite sequence is given by,

$$\{Y_t\} = \{..., y_{-1}, y_0, y_1, y_2, ..., y_t, y_{t+1}, ...\}. \tag{2.1}$$

The observed sample, $y_1, y_2, ..., y_t$ is just one realisation of a section of the stochastic process. Mathematically, each value of Y_t is a random variable defined at that particular time point.

A time series is stationary if the data generating process is time invariant. It is in two forms namely strict stationarity and weak stationarity. A time series, say Y_t, is strictly stationary if the joint probability distribution of Y_t is identical to that of Y_{t+k}. In other words, the process remains stationary even if it is lagged by k periods (Enders, 1995). On the other hand, Y_t is said to be weakly stationary if its mean and all the auto-covariances are independent of time. Thus, a weakly stationary series must satisfy three conditions: (i) $E(Y_t) = \mu$, (ii) $Var(Y_t) = \sigma^2$ and (iii) $Cov(Y_t, Y_{t-k}) = \gamma_k$.

Time series differs from classical statistics in that, for the latter, inferences on the population can be made based on a model, which is estimated using a sample comprising a number of independent records whereas for the former, the observed series is used to fit a model that best approximates the theoretical stochastic process. It is not possible with time series data to obtain multiple time series data of the same process over the same time period since we can not go back in time (Enders, 1995). Assuming the distribution of the series remains stationary, then over time, a number of values from the same distribution are observed, giving a single time series.

2.2 Time Series Tools

Time series analysis uses a number of tools, some of which are given below.

2.2.1 Auto-covariance

Auto-covariance is a measure of linear dependence of variables generated from a single stochastic process. For a process Y_t with a constant mean μ_Y, it is a measure of how much successive $y_t's$ vary together in a linear relationship with its own lags as below (Enders, 1995).

$$Cov(Y_t, Y_{t+k}) = E[(Y_t - \mu_Y)(Y_{t+k} - \mu_Y)]. \tag{2.2}$$

If we calculate the auto-covariance for $k = 0; \pm1; \pm2; ...$, we obtain the auto-covariance function denoted by γ_k, which is an even function of the lag in that $\gamma_k = \gamma_{-k}$. It can either be positive or negative. When $k = 0$, the auto-covariance function reduces to the variance of the process denoted by γ_0.

2.2.2 Autocorrelation Function (ACF)

Auto-covariance is not independent of the units of measure. If the mean and auto-covariance structure does not change over time, we normalise the auto-covariance by dividing by γ_0 to obtain the autocorrelation function given by

$$\rho_k = \frac{\gamma_k}{\gamma_0}, \text{k} = 0, 1, 2, ... \tag{2.3}$$

It measures the length and strength of the memory of the process, that is, the extent to which the value taken at time t depends on the one taken at time $t-k$. Clearly, $\rho_o = 1$. The graph of the ACF versus k is known as the correlogram.

2.2.3 White Noise

White noise is a zero mean discrete-time stochastic process whose terms are independent and identically distributed (IID). It can either be univariate or multivariate. Considering a one dimensional process, the sequence, $\{\epsilon_t\}_{t=-\infty}^{t=\infty}$ is said to be white noise if it satisfies three conditions: (i) $E(\epsilon_t) = 0$, (ii) $Var(\epsilon_t) = \sigma^2$ and (iii) $Cov(\epsilon_t, \epsilon_\tau) = 0$ for all t $\neq \tau$.

2.3 Operators in a Time Sequence

2.3.1 Backward Shift and Difference Operators

The most commonly used operators in time series are the backward shift operator, B and the difference operator, Δ. The backward shift operator is a linear operator which is such that, for a given process Y_t,

$$B^k Y_t = Y_{t-k}. \tag{2.4}$$

Thus, premultiplying Y_t by B^k transforms to lagging Y_t by k periods (Gujarati, 2003; Enders, 1995). Hence, the backshift operator operates on an element of a time series to produce the previous element. It follows then that if B is raised to a negative power, then we will have a lead operator.

The first difference operator, Δ for a stochastic process, say Y_t, is given by $\Delta Y_t = Y_t - Y_{t-1}$ or equivalently, $\Delta Y_t = (1-B)Y_t$. It follows then that we can generalise to the k^{th} difference operator given by $\Delta^k Y_t = (1-B)^k Y_t$.

2.3.2 Auto-regressive Model of order p: $[AR(p)]$

An $AR(p)$ is specified as a weighted average of the $Y_t's$ for the past p periods, together with a white noise error term in the current period. It is given by $y_t = \psi_0 + \psi_1 y_{t-1} + \psi_2 y_{t-2} +$

$... + \psi_p y_{t-p} + \epsilon_t$. In backward shift notation, it can be writen in a more compact form,

$$\Psi(B)y_t = \psi_0 + \epsilon_t \tag{2.5}$$

where $\Psi(B)$ is the lag polynomial $(1 - \psi_1 B - \psi_2 B^2 - ... - \psi_p B^p)$ (Enders, 1995). The process is stationary if the roots of the polynomial lie outside the unit circle. If any root lies on or inside the unit circle, the process is non-stationary and will exhibit apparent trend.

2.4 Random Walk

A random walk is an $AR(1)$ process, often followed by stock price movements. For a series $\{Y_t\}$, it is defined as $Y_t = Y_{t-1} + \epsilon_t$ where ϵ_t is a white noise disturbance term. The process is conventionally started at zero when $t = 1$. The general form is $Y_t = Y_0 + \sum_{i=1}^{t} \epsilon_t$, with a constant mean and a non constant variance. Since Y_t is explained by an initial value plus all the disturbances since the process began, stochastic shocks have nondecaying effects on the $\{Y_t\}$ sequence, often called persistence or long memory.

2.5 Unit Roots

The concept of unit roots is all about differencing non-stationary series an appropriate number of times to make them stationary. Such series are called difference stationary and a classic example is a random walk process, often followed by asset prices such as stock prices and exchange rates (Gujarati, 2003).

2.6 Dickey-Fuller Tests for Unit Roots

Dickey and Fuller (1979, 1981) developed a method to conduct formal tests for the presence of a unit root (Enders, 1995). Their tests are based on an $AR(1)$ model

$$\Delta Y_t = \alpha + \gamma Y_{t-1} + \epsilon_t \tag{2.6}$$

where $\gamma = (\psi_1 - 1)$. The $AR(1)$ model has a factor $1 - \psi_1 B$, so that if there is a unit root, then $\psi_1 = 1$, and so γ will equal zero. The constant, α varies over the three statistics proposed by Dickey and Fuller as follows:

2.6.1 Dickey-Fuller $\hat{\tau}$-statistic

This test uses equation 2.6 for $\alpha = 0$ and is based on the ordinary least squares regression t-statistic for $\gamma = 0$. Its null hypothesis corresponds to the presence of a unit root and the alternative is chosen to maximise the power of the test in the likely direction of departure from the null, that is, $H_A : \gamma < 0$. The test is however too restrictive in that the process could be $AR(p)$ not $AR(1)$. It also imposes a zero mean and does not allow for a trend term.

2.6.2 Dickey-Fuller $\hat{\tau_\mu}$ -statistic

This test allows for a non-zero mean by taking $\alpha = \mu$ and uses the regression equation $\Delta Y_t = \mu + \gamma Y_{t-1} + \epsilon_t$. The null and alternative hypotheses are as in $\hat{\tau}$-statistic but $\alpha = \mu$ is important for the distribution of $\hat{\tau_\mu}$ test. This test is however not appropriate when there is an obvious trend in the series since the model under the alternative has no mechanism to generate that trend. This is so because under $H_0 : \gamma = 0$, equation 2.6 reduces to $\Delta Y_t = \mu + \epsilon_t$ which is a random walk plus drift, and thus, has trend. Under $H_A : \gamma < 0$, the series Y_t in equation 2.6 is stationary around the constant mean, $\frac{\alpha}{1-\psi_1}$ and so, has no trend.

A trend stationary series is one with a deterministic trend responsible for the sustained increase or decrease in the series over time and a white noise disturbance term. Such a series can not be weakly stationary due to the time varying mean. But, if this variation can be adequately explained by some form of deterministic term, the detrended series will be stationary.

2.6.3 Dickey-Fuller $\hat{\tau_\tau}$-statistic

This test allows for a difference stationary null and a trend stationary alternative. It considers $\alpha = \mu + \phi t$ to give the regression equation $\Delta Y_t = \mu + \phi t + \gamma Y_{t-1} + \epsilon_t$. The null is such that $H_0 : (\mu, \gamma, \phi) = (\mu, 0, 0)$. Rejection of the null carries a presumption in favour of the trend stationary model, leaving $H_A : (\mu, \gamma, \phi) = (\mu, \gamma, \phi)$.

2.6.4 Augmented Dickey-Fuller test

Some time series processes may exhibit complex patterns that can not be adequately discribed by an $AR(1)$ process $\Delta Y_t = \mu + \phi t + \gamma Y_{t-1} + \epsilon_t$ (Enders, 1995). For example, the process may be $AR(p)$ and not $AR(1)$. Thus, fitting an $AR(1)$ model would yield $\Delta Y_t = \mu + \phi t + \gamma Y_{t-1} + \upsilon_t$ where υ_t is autocorrelated. We control for this serial autocorrelation by augmenting the model, that is,

$$\Delta Y_t = \mu + \phi t + \gamma Y_{t-1} + \sum_{i=1}^{p} \beta_i \Delta Y_{t-i} + \upsilon_t \tag{2.7}$$

and it is the term, ΔY_{t-i} which "knocks-out" serial correlation. The maximum lag length p is selected using information criteria, which intuitively are operational ways of trading-off the complexity of an estimated model against how well the model fits the data.

2.6.5 Information Criteria

The idea is to minimise a function of the form

$$IC(k) = ln(\hat{\sigma^2}) + C_n, k = 1, 2, ..., k^* \tag{2.8}$$

where IC is information criteria, k^* is the maximum lag the practitioner deems acceptable, n is the number of observations not lost to differencing and $\hat{\sigma^2}$ is the estimated regression error variance of the model. Generally, $\hat{\sigma^2}$ decreases as more lags are added (better fit). On the other hand, C_T is the penalty term for adding more lags. It follows then that the penalty increases as more lags are added. The most commonly used model selection criteria are the Akaike Information Criterion (AIC) and the Schwarz Bayesian Information Criterion (SBC). Their respective specifications are $AIC = nln(\hat{\sigma^2}) + 2k$ and $SBC = nln(\hat{\sigma^2}) + k(ln(n))$.

2.6.6 Unit Roots Tests and Structural Breaks

A structural break occurs when a stationary series experiences a shock that causes it to jump to a new level and remain stationary around the new mean. In the presence of such structural changes in the series, various Dickey-Fuller test statistics are biased towards non-rejection of a unit root (Enders, 1995). This is so because a stationary series that is subject to a structural break may appear to be non-stationary as in figure 2.1. There is a possibility that

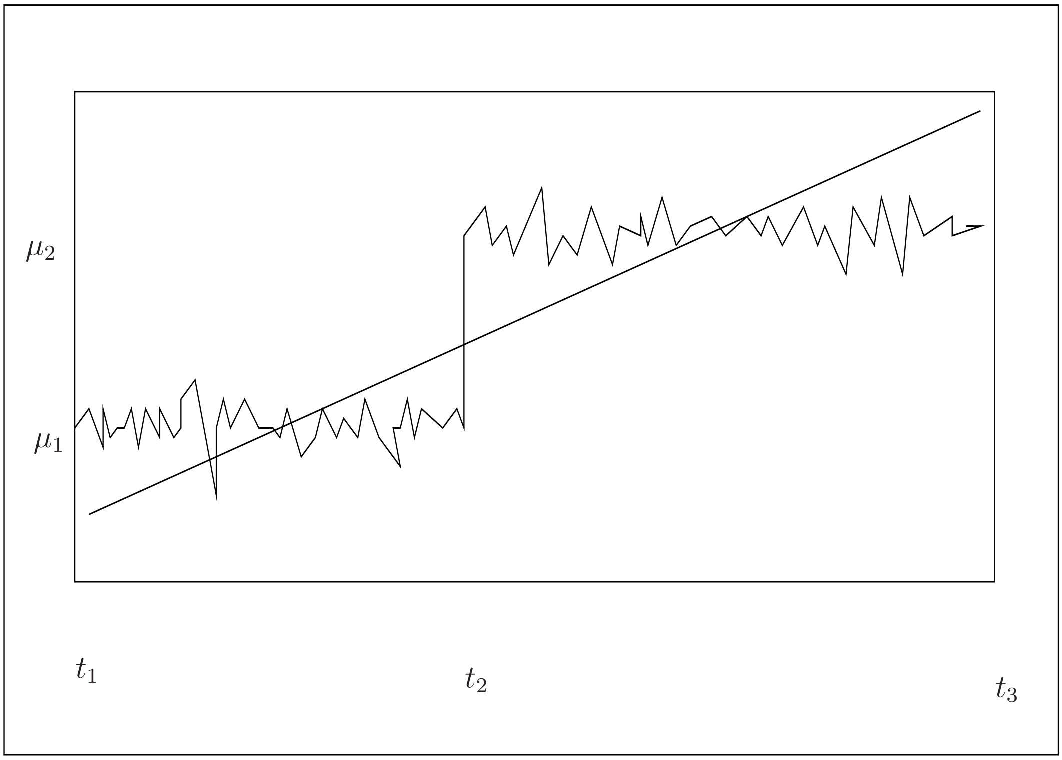


Figure 2.1: A fictitious plot of the sequence constructed by $Y_t = a_0 + a_1 Y_{t-1} + D_L + \epsilon_t$, where D_L is a dummy variable whose level changes and $|a_1| < 1$. For $t \in [t_1, t_2]$, the sequence is stationary around a constant mean μ_1. Following a structural change at time t_2, the sequence jumps and fluctuates around a new constant mean of μ_2 for $t \in [t_2, t_3]$. Since $|a_1| < 1$, the sequence is stationary without the dummy. Ignoring the structural break and fitting $Y_t = a_0 + a_1 Y_{t-1} + \epsilon_t$ gives the best fitting OLS straight line. Thus, the estimated value of a_1 is biased towards 1 and the model approaches a random walk with drift, whose solution includes a deterministic trend.

structural breaks may be relevant to this study, given the changes in the political situation and government economic structure over the time period.

Chapter 3

Possible Models for Estimating Exchange Rate Pass-Through

3.1 Polynomial Distributed-Lag Model

According to Menon (1995), almost all previous researchers used polynomial distributed-lags (PDL) to capture the dynamic responses of traded goods prices to exchange rate changes. The PDL methodology employed ordinary least squares (OLS) to estimate pass-through. In regression analysis involving time series data, a distributed-lag model is one that includes current and lagged (past) values of the explanatory variable. If at least one lagged value of the regressand is part of the regressors, the model becomes an autoregressive model. These two models are widely used in econometric analysis because the dependence of an economic variable on another is rarely instantaneous. Rather, it is very often with a lapse in time, called a lag (Gujarati, 2003).

Assuming finite lags of k_1 and k_2 time periods, a distributed lag is a relation of the form

$$\Delta LP_t = \alpha + \sum_{i=0}^{k_1} \beta_i \Delta LE_{t-i} + \sum_{i=0}^{k_2} \gamma_i \Delta LP^*_{t-i} + \epsilon_t \qquad (3.1)$$

where LP_t is the log of the domestic price of imports, α is a constant, E_t is the nominal exchange rate, and LP^*_t is the corresponding log of the foreign currency price, all in first differences. The constants, β_0 and γ_0 are the short-run multipliers, where as $\sum_{i=0}^{k_1} \beta_i = \beta$

and $\sum_{i=0}^{k_2} \gamma_i = \gamma$ are the long-run multipliers, provided the sums exist, and ϵ_t is a white noise disturbance term.

The Almon distributed-lag approach assumes that β_i and γ_i can be approximated by suitable degree polynomials in i, the length of the lag, as

$$\beta_i = \sum_{h=0}^{p_1} a_h (i - \overline{c_1})^h \tag{3.2}$$

and

$$\gamma_i = \sum_{h=0}^{p_2} b_h (i - \overline{c_2})^h \tag{3.3}$$

for $p_1 < k_1$, $p_2 < k_2$ and $i = 0, 1, 2, ..., k_j$ where $\overline{c_j}$ $(j = 1, 2)$ are pre-specified constants given by

$$\overline{c_j} = \begin{cases} \frac{k_j}{2} & \text{if } k_j \text{ is even} \\ \frac{k_j - 1}{2} & \text{if } k_j \text{ is odd} \end{cases} \tag{3.4}$$

Assuming, for explanation purposes, that second-degree polynomial approximations in i are appropriate, substituting equations 3.2 and 3.3 into equation 3.1 yields

$$\begin{aligned} \Delta LP_t &= \alpha + \sum_{i=0}^{k_1} (a_0 + a_1(i - \overline{c_1}) + a_2(i - \overline{c_1})^2) \Delta LE_{t-i} \\ &\quad + \sum_{i=0}^{k_2} (b_0 + b_1(i - \overline{c_2}) + a_2(i - \overline{c_2})^2) \Delta LP^*_{t-i} + \epsilon_t \\ &= \alpha + a_0 \sum_{i=0}^{k_1} \Delta LE_{t-i} + a_1 \sum_{i=0}^{k_1} (i - \overline{c_1}) \Delta LE_{t-i} + a_2 \sum_{i=0}^{k_1} (i - \overline{c_1})^2 \Delta LE_{t-i} \\ &\quad + b_0 \sum_{i=0}^{k_2} \Delta LP^*_{t-i} + b_1 \sum_{i=0}^{k_2} (i - \overline{c_2}) \Delta LP^*_{t-i} + b_2 \sum_{i=0}^{k_2} (i - \overline{c_2})^2 \Delta LP^*_{t-i} + \epsilon_t \\ &= \alpha + a_0 Z_{0t} + a_1 Z_{1t} + a_2 Z_{2t} + b_0 Z_{3t} + b_1 Z_{4t} + b_2 Z_{5t} + \epsilon_t \end{aligned} \tag{3.5}$$

The constants $\overline{c_j}$ have no effect on the estimates of β_i and γ_i but are included only to avoid numerical problems that can arise from multi-collinearity, a phenomenon inherent in most economic relationships where variables are so highly correlated that it is impossible to come up with reliable estimates of their individual regression coefficients. Multi-collinearity does not affect the ability of a regression equation to predict the response, but poses a real problem if the purpose of the study is to estimate the contributions of individual predictors.

It follows from equation 3.5 that the Almon approach to distributed lags regresses the dependent variable on the constructed variables Z_{it}, not the original regressors. But, if the properties of ϵ_t satisfy the assumptions of the classical linear regression model, then estimates of α, a_i and b_i will have desirable statistical properties. Hence, once we estimate the $a_i's$ and $b_i's$ using OLS, from equation 3.5, the parameters of interest β_i, γ_i and their standard errors can be easily recovered using the relationships described in equations 3.2 and 3.3 since β_i and γ_i are linear transformations of a_i and b_i respectively.

When Almon first introduced the PDL model, she suggested that endpoint constraints must always be employed. The role of endpoint restrictions is to put explicit restrictions on the distributed lag weights outside of their relevant range. They however have no economic or econometric theory, and thus, represent a set of ad hoc restrictions whose sole purpose is to increase estimation efficiency.

3.2 Vector Error Correction Models (VECMs)

Vector error correction models specify the short-run adjustment processes of each variable in the system of equations in a way that captures the dynamics to long-run equilibrium relationships suggested by economic theory. The existence of such long-run relationship however does not prevent the existence of stationary, though variable, short-run deviations from equilibrium. They are best explained by starting with vector autoregressive (VAR) models as follows.

3.2.1 Introduction to Vector Autoregressive (VAR) models

Vector autoregressive models are econometric models used to capture the evolution and the interdependencies between multiple time series. They are a generalisation of the univariate autoregressive models. In a VAR, all the variables are treated symmetrically by including for each variable, an equation explaining its evolution based on its own lags and the lags of all the other variables in the model. According to Enders (1995), multi-equation time series models are now one of the rich areas of time series research. Assuming a two variable case, say $\mathbf{Y_t} = (Y_{1t}, Y_{2t})$, let the time paths of Y_{1t} and Y_{2t} be affected by current and past realisations of each other to give a simple bivariate system:

$$\begin{pmatrix} 1 & g_{12} \\ g_{21} & 1 \end{pmatrix} \begin{pmatrix} Y_{1t} \\ Y_{2t} \end{pmatrix} = \begin{pmatrix} \gamma_{10} \\ \gamma_{20} \end{pmatrix} + \begin{pmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{22} \end{pmatrix} \begin{pmatrix} Y_{1t-1} \\ Y_{2t-1} \end{pmatrix} + \begin{pmatrix} \epsilon_{1t} \\ \epsilon_{2t} \end{pmatrix}$$

or alternatively in a more compact form as

$$\mathbf{GY_t} = \mathbf{\Gamma(0)} + \mathbf{\Gamma(1)}\mathbf{Y_{t-1}} + \epsilon_\mathbf{t} \tag{3.6}$$

where $\epsilon_\mathbf{t}$ is a vector of white noise disturbances which are pure structural inovations (shocks) with economic meaning. This is because if the series Y_{2t} is say the logarithm of the nominal effective exchange rate, then ϵ_{2t} will be the exchange rate shock. Thus,

$$\begin{pmatrix} \epsilon_{1t} \\ \epsilon_{2t} \end{pmatrix} \sim iid \left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_1^2 & 0 \\ 0 & \sigma_2^2 \end{pmatrix} \right]$$

This simple system constitutes a $first-order$ vector autoregression (VAR) since the highest lag length is one. It is called the structural or primitive form of the VAR. The structural VAR incorporates feedback since Y_{1t} and Y_{2t} are explanatory variables of each other. Hence, equations in this system cannot be directly estimated because explanatory variables are correlated with error terms.

3.2.2 Reduced Form VAR

Assuming $\mathbf{G^{-1}}$ exists, equation 3.6 can be writen as $\mathbf{Y_t} = \mathbf{\Phi D} + \mathbf{\Pi_1 Y_{t-1}} + \mathbf{e_t}$, and can be generalised to an $n-variate$ levels VAR(p) process of the form

$$\mathbf{Y_t} = \mathbf{\Phi D} + \mathbf{\Pi_1 Y_{t-1}} + ... + \mathbf{\Pi_p Y_{t-p}} + \mathbf{e_t} \tag{3.7}$$

where $\mathbf{Y_t}$ is the $(n \times 1)$ vector of variables which are potentially co-integrated, $\mathbf{D}$ is an $n \times 1$ vector of deterministic terms, $\mathbf{\Pi_i}$ are $(n \times n)$ matrices of coefficients and $\mathbf{e_t}$ is a vector of normally distributed random processes. It is important to note that reduced form errors are linear combinations of structural form errors since $\mathbf{e_t} = \mathbf{G^{-1}}\epsilon_\mathbf{t}$, and have no economic meaning. The covariance matrix of the reduced form errors is given by:

$$\begin{aligned} E[\mathbf{e_t}\mathbf{e_t}'] &= E[(\mathbf{G^{-1}}\epsilon_\mathbf{t})(\mathbf{G^{-1}}\epsilon_\mathbf{t})'] \\ &= \mathbf{G^{-1}}\mathbf{E}[\epsilon_\mathbf{t}\epsilon_\mathbf{t}'](\mathbf{G^{-1}})' \\ &= \frac{1}{(1-g_{12}g_{21})^2}\begin{bmatrix} \sigma_1^2 + g_{12}^2\sigma_2^2 & -(g_{21}\sigma_1^2 + g_{12}\sigma_2^2) \\ -(g_{21}\sigma_1^2 + g_{12}\sigma_2^2) & \sigma_2^2 + g_{21}^2\sigma_1^2 \end{bmatrix} \end{aligned} \tag{3.8}$$

This shows that reduced form errors are not necessarily uncorrelated as long as g_{12} and g_{21} are non-zero.

3.2.3 Co-integration

The idea of non-stationary variables sharing a stationary equilibrium relation was first formalised by Engle and Granger (1987). They used the term "co-integration" to denote this property, signifying co-movements among trending variables. Consider our two time series, Y_{1t} and Y_{2t} and assume that they are integrated of the same order, say d, denoted $I(d)$ ($d = 1$ for most econometric time series). The disequilibrium error at time t is given by

$$Y_{1t} - \varphi_2 Y_{2t} = \xi_t. \tag{3.9}$$

If Y_{1t} and Y_{2t} are "bound together over time" in an equilibrium relationship governed by φ_2, ξ_t is expected to be a zero mean stationary process even if neither of Y_{1t} and Y_{2t} is. In this statistical sense, the concept of co-integration mimics the existence of a long-run equilibrium to which the system converges. According to Enders (1995), any deviation from long-run equilibrium in equation 3.9 is ξ_t and since ξ_t is stationary, such a deviation is only temporary. This follows from the fact that any shock to a stationary series will cause it to jump but it will eventually return to its trend pattern. Thus, the relationship between Y_{1t} and Y_{2t} is of error correction form, in that if any of them drifts away from equilibrium, the system will adjust and bring it back to equilibrium.

Equation 3.9 can be written as

$$Y_{1t} = \varphi_1 + \varphi_2 Y_{2t} + \zeta_t \tag{3.10}$$

where φ_1 is the introduced constant and $\zeta_t = \xi_t - \varphi_1$. A natural co-integration test is based on the properties of ζ_t in that if ζ_t is $I(0)$, then Y_{1t} and Y_{2t} are co-integrated.

The Engle-Granger (1987) approach demonstrates that residuals from the regression of an $I(1)$ variable on another $I(1)$ variable can be subjected to a unit root test, the null of which is no co-integration. This is achieved from the following steps:

(1) Assess the integration order of Y_{1t} and Y_{2t} separately using unit root test.

(2) Regress Y_{1t} on Y_{2t} (or vice versa) to obtain $\hat{Y_{1t}} = \hat{\varphi}_1 + \hat{\varphi}_2 Y_{2t}$.

(3) Estimate ζ_t from $\hat{\zeta_t} = Y_{1t} - \hat{Y_{1t}}$.

(4) Run an augmented Dicky-Fuller test on $\hat{\zeta_t}$ to assess its order of integration.

If the null hypothesis cannot be rejected, then Y_{1t} and Y_{2t} do not co-integrate. Otherwise they are co-integrated and we write $(Y_{1t}, Y_{2t}) \sim CI(d, b)$ where d is their common order of cointegration and b is the reduction in the order of integration of the co-integrating combination. This approach is only suitable when there is a single co-integration vector.

A useful way to understand co-integration relationships is Stock and Watson's (1988) observation that co-integrated variables share common stochastic trends. If we disregard cyclical and seasonal terms in our two series Y_{1t} and Y_{2t} (each supposedly $I(1)$), the series can be decomposed into a random walk ($I(1)$ component) and an $I(0)$ variable ϵ_{it} ($i = 1, 2$), not necessarily white noise (Enders, 1995).

We can write the two series as $Y_{1t} = h_{1t} + \eta_{1t}$ and $Y_{2t} = h_{2t} + \eta_{2t}$ since the sum of an $I(1)$ and an $I(0)$ series is generally $I(1)$, meaning we retain the properties of Y_{1t} and Y_{2t}. Assuming $(Y_{1t}, Y_{2t}) \sim CI(1, 1)$, there must exist non-zero values of φ_1 and φ_2 for which $\varphi_1 Y_{1t} + \varphi_2 Y_{2t}$ is stationary. That is:

$$\begin{aligned} \varphi_1 Y_{1t} + \varphi_2 Y_{2t} &= \varphi_1(h_{1t} + \eta_{1t}) + \varphi_2(h_{2t} + \eta_{2t}) \\ &= (\varphi_1 h_{1t} + \varphi_2 h_{2t}) + (\varphi_1 \eta_{1t} + \varphi_2 \eta_{2t}) \end{aligned} \tag{3.11}$$

Thus, the linear combination $\varphi_1 Y_{1t} + \varphi_2 Y_{2t}$ can only be stationary if $(\varphi_1 h_{1t} + \varphi_2 h_{2t})$ vanishes, meaning the necessary and sufficient condition for Y_{1t} and Y_{2t} to be $CI(1,1)$ according to Enders (1995) is

$$\varphi_1 h_{1t} + \varphi_2 h_{2t} = 0. \tag{3.12}$$

Realised values of h_{1t} and h_{2t} change with time and since $\varphi_i \neq 0$, equation 3.12 is true for all t if and only if $h_{1t} = \frac{-\varphi_2}{\varphi_1} h_{2t}$. This means that up to the scalar $\frac{-\varphi_2}{\varphi_1}$, Y_{1t} and Y_{2t} must have the same stochastic trend if they are to be co-integrated.

If the variables in the p^{th} order $n-variate$ VAR in equation 6.2.2 are co-integrated, the co-integrating relations become apparent if it is re-parameterised into a vector error correction model (VECM). This is achieved by subtracting $\mathbf{Y_{t-1}}$ from both sides and rearranging terms (Hamilton, 1994; page 580) to yield

$$\mathbf{\Delta Y_t = \Phi D + \Pi Y_{t-1} + \Gamma(1)\Delta Y_{t-1} + ... + \Gamma(p-1)\Delta Y_{t-p+1} + e_t} \tag{3.13}$$

where $\mathbf{\Pi} = (\mathbf{\Pi_1} + \mathbf{\Pi_2} + ... + \mathbf{\Pi_p} - \mathbf{I_n})$ and $\mathbf{\Gamma(i)} = -\sum_{\mathbf{j=i+1}}^{\mathbf{p}} \mathbf{\Pi_j}$, for $i = 1, 2, ..., p-1$. Since it is assumed that $\mathbf{\Delta Y_t}$ and $\mathbf{e_t}$ are $I(0)$, then $\mathbf{\Pi Y_{t-1}}$ must also be $I(0)$ because a non-stationary variable cannot explain a stationary one.

3.3 Autoregressive Distributed Lag models

Another class of models for estimating exchange rate pass-through is the autoregressive distributed lag model (ARDL), considered to be the major workhorse in dynamic single-equation regressions (Hassler and Wolters, 2005). For the series LP_t and lag oders p and q, the ARDL(p,q) is defined as

$$LP_t = \alpha_0 + \sum_{i=1}^{p} \pi_i LP_{t-i} + \sum_{i=0}^{q} \mathbf{c_i}'\mathbf{X_{t-i}} + \epsilon_t \tag{3.14}$$

where α_0 is a constant term, π_i are scalar coefficients, $\mathbf{c_i}'$ are row vectors and $\mathbf{X_{t-i}}$ is a 2-dimensional column vector process specified as $\mathbf{X_{t-i}} = [LE_t, LP_t^*]'$ in this case. In lag operator form and neglecting the constant term for brevity, equation 3.14 can be written as

$$\pi(L)LP_t = \mathbf{c}'(\mathbf{L})\mathbf{X_t} + \epsilon_t \tag{3.15}$$

where $\pi(L) = 1 - \pi_1 L - ... - \pi_p L^p$ is the lag polynomial and $c(L) = c_0 + c_1 L + ... + c_n L$ is the vector polynomial.

3.3.1 ARDL models and Error Correction Models

According to Hendry (1995), every type of single-equation model in empirical time series econometrics is a special case of an ARDL(1,1). Thus, we will consider a simple ARDL(1,1) model specified as

$$LP_t = \alpha_0 + \pi_1 LP_{t-1} + \theta_0 LE_t + \theta_1 LE_{t-1} + \omega_0 LP_t^* + \omega_1 LP_{t-1}^* + \epsilon_t. \tag{3.16}$$

If LP_s, LE_s and LP_s^* are steady-state equilibrium values, then

$$LP_s = \frac{\alpha_0}{1-\pi_1} + \frac{\theta_0 + \theta_1}{1-\pi_1} LE_s + \frac{\omega_0 + \omega_1}{1-\pi_1} LP_s^* \tag{3.17}$$

Taking partial derivatives with respect to LE_s and LP_s^* gives $\lambda_1 = \frac{\theta_0+\theta_1}{1-\pi_1}$ and $\lambda_2 = \frac{\omega_0+\omega_1}{1-\pi_1}$ as the respective long-run derivatives. Subtracting LP_{t-1} from both sides of Model 3.16 followed by adding and subtracting $\theta_0 LE_{t-1}$ and $\omega_0 LP_{t-1}^*$ on the right hand side yields the error correction model (ECM)

$$\begin{aligned}
\Delta LP_t &= \alpha_0 + (\pi_1 - 1)LP_{t-1} + \theta_0 LE_t + \theta_0 LE_{t-1} - \theta_0 LE_{t-1} + \theta_1 LE_{t-1} \\
&\quad + \omega_0 LP_t^* + \omega_0 LP_{t-1}^* - \omega_0 LP_{t-1}^* + \omega_1 LP_{t-1}^* + \epsilon_t \\
&= \alpha_0 + (\pi_1 - 1)LP_{t-1} + \theta_0 \Delta LE_t + (\theta_0 + \theta_1)LE_{t-1} + \omega_0 \Delta LP_t^* \\
&\quad + (\omega_0 + \omega_1)LP_{t-1}^* + \epsilon_t \\
&= \alpha_0 + (\pi_1 - 1)LP_{t-1} + \theta_0 \Delta LE_t - \lambda_1(\pi_1 - 1)LE_{t-1} + \omega_0 \Delta LP_t^* \\
&\quad - \lambda_2(\pi_1 - 1)LP_{t-1}^* + \epsilon_t \\
&= \alpha_0 + \alpha_1(LP_{t-1} - \lambda_1 LE_{t-1} - \lambda_2 LP_{t-1}^*) + \theta_0 \Delta LE_t + \omega_0 \Delta LP_t^* + \epsilon_t
\end{aligned} \tag{3.18}$$

The term, $(LP_{t-1} - \lambda_1 LE_{t-1} - \lambda_2 LP_{t-1}^*)$ is the error correction term and α_1 measures the speed with which ΔLP_t adjust towards equilibrium. Hence, if the series are co-integrated, the ECM is a special case of an ARDL model.

3.3.2 ARDL models and PDL Models

On the other hand, the ARDL model for import prices that includes the nominal effective exchange rate and foreign price in first differences to avoid spurious regressions takes the form

$$\Delta LP_t = \alpha_0 + \sum_{i=1}^{p} \pi_i \Delta LP_{t-i} + \sum_{i=0}^{q} \theta_i \Delta LE_{t-i} + \sum_{i=0}^{q} \omega_i \Delta LP^*_{t-i} + \epsilon_t. \tag{3.19}$$

Some applied researchers favour the subclass of model 3.19, namely models with no lagged values of the dependent variable (Panopoulou and Pittis, 2004). This gives the model

$$\Delta LP_t = \alpha_0 + \sum_{i=0}^{q} \theta_i \Delta LE_{t-i} + \sum_{i=0}^{q} \omega_i \Delta LP^*_{t-i} + \epsilon_t. \tag{3.20}$$

If θ_i and ω_i are restricted to some lower degree polynomials and the maximum lag, q is not necessarily fixed, then equation 3.20 reduces to a PDL model which, according to Mbaga and Coyle (2003), is a more restrictive dynamic model. Thus, ECMs and PDL models are special cases of the ARDL model.

Chapter 4

Literature Review

Several economic policy issues, notably monetary policy designs and balance of payments adjustment processes, depend on the determination of the rate at which exchange rates pass through to prices (De Bandt et al, 2007). Included are issues relating to pricing strategies of foreign exporting firms, prolonged inflation, inflation forecasting success and the impact of entering into a monetary union as is the case with the European union countries. In response to the importance of the pass-through issue, a sizeable literature has developed.

The early literature surveyed by Menon (1995) covers 43 studies on the pass-through issue. Of these, 16 examine the pass through to import prices, 10 to export prices, 13 to both import and export prices and 3 to domestic producer prices. The survey identified some issues requiring closer attention namely country coverage, estimation methods and findings.

4.1 Country Coverage

Most early work on pass-through concentrated on larger economies like the US, Japan and Germany. In fact, more than 50 percent of the available pass-through estimates are from these 3 countries, meaning that smaller and more trade dependent economies have received less coverage (Menon, 1995). This view is also supported by Goldberg and Knetter (1997) who report that the analysis of pass-through for the US dominated most exchange rate pass-through research in the 1980s. McCarthy (2002) also concentrated on industrialized countries.

The few studies examining pass-through for small open economies are in a multi-country context. This makes the pass-through estimates unreliable, both for each of the combined countries and for the smaller economies in general. Recently, a few studies have focussed on the Euro zone, following its creation in 1999. In particular, Campa and Minguez (2006) consider pass-through into disaggregated import prices in the Euro zone. They used time series data on import unit values for 13 different product categories for each destination country, but did not address the issue at aggregate level.

4.2 Estimation Methods from Previous Studies

The majority of early researchers on the pass-through subject, according to Menon (1995) employed methods such as polynomial distributed lags that used conventional ordinary least squares as an estimation technique. Such methods however, have not accounted for the time series properties of the data. In particular, Nelson and Plosser (1982) suggest that macroeconomic series such as exchange rates are non-stationary, meaning that using OLS to estimate a regression with such data may lead to the problem of 'spurious regressions', a phenomenon where regressing an integrated but completely unrelated variable on another may yield statistical significance when, in fact, the relation is completely meaningless.

Menon (1995) further criticizes these previous studies for paying little attention to model evaluation using diagnostic checks. They focussed mainly on reporting standard summary statistics and ignored important tests for possible regression mis-specification and exogeneity of the regressors. The implication therefore is that such models may be subject to misspecification errors, meaning that previous estimates of pass-through may be biased.

Of late, however, empirical work on exchange rate pass-through has tried to improve on the deficiencies of earlier studies identified by Menon (1995). A comprehensive study is given by McCarthy (2002), who investigates exchange rate pass-through on the aggregate level for selected industrialized economies. Rangasamy and Farrell (2002) also point to the now widely acknowledged belief that non-stationary series such as exchange rates and trade prices are potentially co-integrated, implying that estimation techniques must allow for co-integration. By design, co-integration analysis is inherently multivariate since a single time series can not be co-integrated. Barhoumi (2006) implemented a different method of analysis which employs new panel co-integration techniques and can reveal a possible co-integration relationship among several variables. We however will not use this technique in this research report since we are using aggregate data.

More modern studies suggest using a co-integration approach to model the pass-through relationship. Such techniques include the Engle-Granger (1987) and the Johansen (1988) approaches to co-integration analysis. According to Pahlavani, Wilson and Worthington (2005), studies by Pesaran and Pesaran (1997), Pesaran and Smith (1998) and Pesaran, Shin and Smith (2001) introduced an alternative technique called the Autoregressive Distributed Lag co-integration approach. Unlike the Johansen approach, it is relatively more efficient in small or finite data samples, does not force regressors to be integrated of the same order (provided they are not $I(2)$ or higher) and avoids a number of choices like variables to be included in the VAR, determination of the the VAR lag length and treatment of deterministic elements.

4.3 Findings from Previous Studies

We give below a summary of what past work has found and concluded on the exchange rate pass through subject, paying particular attention to: (i) the degree and dynamics of exchange rate pass-through, (ii) exchange rate pass-through patterns across countries and (iii) diversity in pass-through estimates across studies for a single country.

4.3.1 The Degree and Dynamics of Exchange Rate Pass-Through

The majority of studies conclude that incomplete pass-through is a common phenomenon across a wide range of countries studied. They also found that this partial pass-through process takes a number of lags to occur. Citrin (1989), Lawrence (1990) and Leith (1991) report that only 13 percent of studies report complete or close to complete pass-through. These few studies finding full or near complete pass-through further report even longer lags at which changes in exchange rates are passed-through to prices. In particular, Leith (1991) reports lags in the transmission of exchange rates to prices of up to 5 quarters.

The literature examined by Darvas (2001) did not give an explanation for the incomplete nature of exchange rate pass-through, but only acknowledged its existence. The explanation for incomplete pass-through, as it was forcefully put by Magee (1975), has no single coherent theory of devaluation (or revaluation), but is rather an amalgam of reasons as to why prices may not respond fully to exchange rate changes. Campa and Minguez (2006) hold that incomplete pass-through is due to the degree of openness of countries to imports. This belief was also echoed by Barhoumi (2006), in addition to exchange rate and inflation regimes as factors behind incomplete exchange rate pass-through. On the contrary, Brissimis and Kosma (2007) believe there is a relationship between market power (measured by market share) and incomplete exchange rate pass-through assuming imperfectly competitive markets. The implication is that incomplete pass-through is partly due to imperfect competition in international markets.

Recent theoretical literature builds almost exclusively on the concept of market segmentation, a situation where transaction terms for otherwise identical products are substantially influenced by the location of buyers and sellers. On the whole, however, incomplete pass-through is not necessarily evidence of a lack of market integration. Menon (1995) and Hens (1997) argue that, even if there were perfect competition and product homogeneity, the pass-through may still be different due to non-zero price elasticity of demand and the supply side effects of exchange rate changes.

4.3.2 Exchange Rate Pass-Through Patterns Across Countries

Regarding pass-through across countries, significant differences have been found. According to Kreinin (1977), exchange rate pass-through estimates range from as low as 50 percent for the US to complete pass through for Italy. There is, however, no consensus to explain these differences but it is believed that openness and country size are influential factors. The findings of Kreinin (1977) point to the fact that the rate at which the exchange rate changes pass-through to prices vary inversely with the size of the country. On the contrary however, Khosla and Teranish (1989) find complete pass-through for large countries like the US and Japan, but very low pass-through for smaller economies such as Indonesia and the Philippines, suggesting a direct proportional relationship with country size. This view is supported, to some extent, by Spitaeller (1980) who finds complete pass-through for the US but not for Germany.

4.3.3 Exchange Rate Pass-Through Across Studies for a Given Country

Different pass-through studies for a specific country surprisingly yielded significant differences in the estimates. This is particularly so for the US, which is by far the most often studied country. Menon (1995) surveyed 7 studies estimating the aggregate pass through of changes in exchange rates to import prices in the US over roughly the same period and on almost similar commodities, beginning around 1970 up to between 1986 and 1988. The differences in the estimates from these studies is quite significant, ranging from a low of 48.7 percent (Alterman, 1991) to a high of 91 percent (Helkie and Hooper, 1988). According to Menon (1995), these differences are largely due to the use of different methodologies, model specifications and variable selection, since the time period and commodities were held almost constant.

Chapter 5

Methodology

We build on the reviewed literature and examine two methodologies for estimating the pass-through of exchange rate changes to South Africa's import prices. They are: (i) a Polynomial distibuted-lag (PDL) model and (ii) the Johansen-type vector error correction model (VECM). We settled for these two models because both are submodels of the ARDL model as explained in Chapter 3. As a result, this provides a basis for comparing them via a simulation study since we have a general model from which to simulate the data, without disadvantaging any of the two models under comparison. Further, the choice of the two models also enables us to compare the performance of a more statisticaly oriented distributed lag model (without much econometric interpretation) against a rather more econometrically oriented error correction model (with econometric implications) for estimating exchange rate pass-through. The Johansen-type VECM was also used by Rangasamy and Farrell (2002) and this work is in comparison with theirs, although we extend the work by also looking at a longer series and by carrying-out model comparison.

5.1 Estimating Polynomial (Almon) Distributed-Lag Models

A polynomial distributed lag (PDL) model is specified in Eviews by the `pdl` term and any number of `pdl` terms (corresponding the number of regressors) may be included in the estimation equation. Specification of the PDL model in Eviews requires information on:

(1) The name of the series.

(2) The lag length (the number of lagged values of the series to be included).

(3) The degree of the polynomial.

(4) An optional numerical code to constrain the ends of the lag polynomial to zero.

The maximum length of the lags must be specified in advance. A possible way is to use the general-to-specific approach. This entails starting with a very large value of the lag length k_j, and seeing if the fit of the model deteriorates significantly when it is reduced with no restrictions on the shape of the distributed lag. Alternatively, information criteria may be used to choose an appropriate lag length.

Having specified the values of the lag lengths k_j, the degree of the polynomials p_j must also be specified. In general, p_j should be at least one more than the number of turning points in the curve relating β_i and γ_i to i. However, the number of such turning points is not known a priori, making the choice of p_j largely subjective. In some cases, theory may suggest a particular shape, though in practice, a fairly low degree polynomial (say p_j=2 or 3) may give good results.

Finally, the optional numerical code for constraining the lag polynomial has three options. They are (i) constrain the near end of the lag to zero, (ii) constrain the far end or (iii) constrain both ends. The last is to restrict the effects of the regressors to die-off beyond the number of specified lags whilst the former restricts the one-period lead effects of regressors to zero.

5.2 Johansen-type Vector Error-correction Models

The choice of the Johansen-type vector error-correction models (VECMs) to estimate equation 1.3 is motivated by the fact that, unlike the Engle-Granger (1987) approach, which is not a structural relationship (any variable can be the regressand), it is based on a relevant economic model. Further, the Engle-Granger (1987) approach cannot estimate more than one cointegrating vector, or even establish their existence.

Vector error-correction models exploit the link which co-integration provides between vector autoregressive models (VARs), first used by Sims (1980) and error-correction models (ECMs) of Davidson, Hendry, Srba and Yeo (1978). The Johansen procedure follows three major steps which are:

(1) Pretests and VAR lag length selection.

(2) Model estimation and determination of the rank of Π.

(3) Analysis of the normalised cointegration vector(s) and speed of adjustment coefficients.

5.2.1 Pretests and VAR Lag Length Selection

Pretests are useful for assessing the order of integration of the variables under consideration. To use the Johansen approach, all the variables must have the same order of integration. A visual analysis of the time series plot of the data is always a logical first step in any time series analysis. We get some insight regarding the behaviour of the series from such plots, particularly the possibility of a linear time trend in the data generating process (Enders, 1995). As a rough guide to establishing the integration order of the variables, visual inspection of the ACFs and PACFs may be used. For instance, when the ACF is "tailing-off" to zero, it may be caused by (i) a large characteristic root, (ii) a pure unit root process or (iii) a trend stationary process.

Formal tests such as standard Augmented Dickey-Fuller tests are then required to establish the order of integration for the variables. However, special care must be taken if a structural break has occurred since the Dickey-Fuller test statistics will be biased toward the nonrejection of a unit root. According to Enders (1995), an econometric procedure to test for unit roots when a structural break has occurred, is to split the series into two subperiods and use Dickey-Fuller tests on each subperiod. The drawback of this procedure is the severe reduction of degrees of freedom for each of the resulting regressions, meaning a single test based on the full series may be preferable. Another possibility is to account for the structural break by including a dummy series D_L as in Figure 2.1 where $D_L = 0$ for $t \in [t_1, t_2]$ and $D_L = \mu_2 - \mu_1$ for $t \in [t_2, t_3]$ and to test for its statistical significance. This requires pre-specification of t_2

Having determined the integration order of the variables, the next step is to determine the important interrelationships among the variables. This is based on Sims (1980) VAR analysis which allows for co-movements in the data such as the possibility of co-integrating relationships. This entails determining the variables to enter the VAR and selecting the appropriate lag length of the VAR. The former is achieved by using a relevant economic model, which in our case is equation 1.9 indicating that all variables need to be included in the VAR. Information criteria, which are trade-offs between goodness of fit and parsimony, are then used for the latter. Examples of information criteria include final prediction error (FPE), Akaike (AIC), Schwarz Bayesian (SBC) and Hannan-Quinn (HQ).

5.2.2 Model Estimation and the Number of Cointegrating Vectors

The specified VAR(p) model may be estimated in three forms: (i) with all deterministic terms set to zero, (ii) with a drift or (iii) with a constant term in the co-integrating vector. Having estimated the VAR model, its adequacy is tested through a careful study of the residuals, called diagnostic checking. In particular, if the selected lag length is correct, we expect the residuals to behave like white noise; otherwise they contain information we would prefer to be captured in the fitted model. Hence, it is very important that the residuals be serially uncorrelated.

Further diagnostic checks include tests for statistical independence and multivariate normality of residuals. The former is tested using residual autocorrelation plots-the autocorrelations should lie within the 95% confidence limits if they are to be statistically independent. The latter however is usually violated in most financial data and can be visually tested by histogram plots of the residuals. Above all, the specified co-integrated VAR (p) model in equation 6.2.2, repeated here for convenience,

$$\mathbf{Y_t} = \mathbf{\Phi D} + \mathbf{\Pi_1 Y_{t-1}} + ... + \mathbf{\Pi_p Y_{t-p}} + \mathbf{e_t}$$

is required to be stable and covariance stationary. This is so if $|\mathbf{I_n} - \mathbf{\Pi_1 z} - ... - \mathbf{\Pi_p z^p}| = \mathbf{0}$ has all roots (eigenvalues) outside the unit circle.

To find the number of co-integrating vectors, assume the variables in equation 6.2.2 are $I(d)$. If they are co-integrated, then their linear combination has a lower order of integration. If the co-integrating relations exist, they must be contained in $\mathbf{\Pi Y_{t-1}}$ from equation 3.13. This would ensure that all the terms in the VECM in equation 3.13 are stationary. Parameters of $\mathbf{\Gamma(i)}$ contain information about the short-run adjustment processes whereas the matrix $\mathbf{\Pi}$

gives coefficients which result in the $I(d)$ $\mathbf{Y_t}$ variables forming $I(0)$ linear combinations.

A fundamental result to the Johansen approach is that, if there are r co-integrating relationships between the variables in the vector $\mathbf{Y_t}$, then $\mathbf{\Pi}$ will be of reduced rank. Hence, it is the rank of $\mathbf{\Pi}$, which is assumed to be r $(0 < r < n)$ that determines the long-run equilibrium relationships. Thus, testing the number of co-integrating relationships is equivalent to testing the rank of $\mathbf{\Pi}$. It follows then that $\mathbf{\Pi}$ can be decomposed into two $(n \times r)$ matrices of rank r as $\alpha\beta'$. The columns of β provide the r co-integration vectors ("co-integrating matrix") whilst the elements of α distribute the impact of the co-integrating vectors to the evolution $\mathbf{\Delta Y_t}$ ("loading matrix") (Rangasamy and Farrell, 2002). Writing $\mathbf{\Pi}$ in this decomposed form transforms equation 3.13 to

$$\mathbf{\Delta Y_t} = \mathbf{\Phi D} + \alpha\beta'\mathbf{Y_{t-1}} + \mathbf{\Gamma(1)\Delta Y_{t-1}} + ... + \mathbf{\Gamma(p-1)\Delta Y_{t-p+1}} + \mathbf{e_t} \tag{5.1}$$

where $\beta'\mathbf{Y_{t-1}}$ is approximately $I(0)$ since β' is a matrix of co-integrating vectors.

The factorization, $\mathbf{\Pi} = \alpha\beta'$ is however not unique. This is so because for any $(r \times r)$ nonsingular matrix $\mathbf{H}$, we have

$$\begin{aligned} \alpha\beta' &= \alpha\mathbf{HH^{-1}}\beta' \\ &= (\alpha\mathbf{H})(\beta\mathbf{H^{-1'}})' \\ &= \alpha^*\beta^{*'} \end{aligned} \tag{5.2}$$

Hence, the factorization only identifies the space spanned by the co-integrating relations, meaning further restrictions on the model are required to obtain unique values of α and β'. Overal, the rank of $\mathbf{\Pi}$ equals the number of its non-zero eigenvalues and the Johansen methodology provides inference on this number.

There are two tests for the number of co-integration relationships, one of which is the Trace test whose test statistic is

$$\lambda_{trace}(r) = -T\sum_{i=r+1}^{n} ln(1-\hat{\lambda}_i) \tag{5.3}$$

where (i) $\hat{\lambda}_i$ is the estimated values of the characteristic roots (eigenvalues) obtained from the estimated matrix $\mathbf{\Pi}$, (ii) T is the number of usable observations and (iii) n is the number of characteristic roots (Enders, 1995). The hypotheses to be tested are

H_0: Co-integrating vectors $\leq r$ versus H_1: Co-integrating vectors $\geq r+1$.

The second test is the Maximum eigenvalue test whose test statistic is given by

$$\lambda_{max}(r, r+1) = -Tln(1 - \hat{\lambda_{r+1}}) \tag{5.4}$$

where r is the number of co-integrating vectors. The hypotheses to be tested are
H_0: There are r Co-integrating vectors versus H_1: There are $r+1$ Co-integrating vectors.

5.2.3 Analysis of the Normalised Co-integration Vectors and Speed of Adjustment Coefficients

We have seen that the co-integration vector, β is not unique. As a result, some normalisation assumption is required for it to be uniquely identified. For our trivariate co-integrated system with a single co-integrating vector, the normalised co-integration vector is of the form $\beta = (\mathbf{1}, -\beta_{\mathbf{1}}, -\beta_{\mathbf{2}})^{'}$ so that

$$\beta^{'}\mathbf{Y_t} = LP_t - \beta_1 LE_t - \beta_2 LP_t^* \tag{5.5}$$

which is approximately integrated of order zero. On the other hand, the elements of the vector α in $\mathbf{\Pi} = \alpha\beta^{'}$ are such that $-1 \leq \alpha_i < 0$ and have the interpretation of the speed of adjustment coefficients, measuring the speed with which $\Delta\mathbf{Y_t}$ adjusts towards equilibrium.

Chapter 6

Data Analysis and Results

We begin by fitting the PDL and Johansen type vector error correction models to the shorter data set, the sample from January 1980 to December 2001. We chose this sample primarily because Rangasamy and Farrell (2002) used it to estimate the long-run exchange rate pass-through into South Africa's import prices. They used the Johansen-type VECM, one of the models under comparison. This provides the basis for us to see if we can reproduce their results.

6.1 Fitting the Polynomial Distributed Lag Model

The polynomial distributed lag (PDL) model assumes that successive coefficients (weights) of each lagged variable of an equation lie on a polynomial. It imposes a smoothness condition (requiring that the coefficients lie on a polynomial of relatively low degree) on the lag coefficients, thereby reducing the number of parameters to be estimated. The rationale behind using the PDL model is that it increases the precision of estimates assuming the correct lag length and degree of the polynomial are specified.

A logical first step in any time series econometric analysis is to visually analyse the time series plots of the data. We work with data in first differences here to avoid running the risk of spurious results. Figure 6.1 gives a time series plot of the logged series in first differences. The series ΔLP_t, ΔLE_t and ΔLP_t^* are all stationary around a mean of zero. After trying several specifications using the general-to-specific approach described in section 5.1 and the

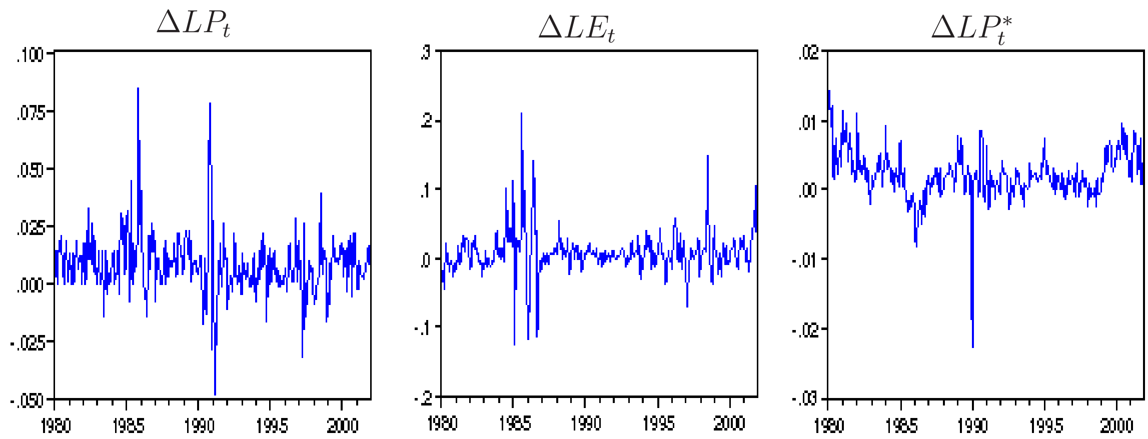


Figure 6.1: Time series plots of the differenced logged series

significance of the parameter estimates of the derived variables as the criterion, we settled for a PDL model with two pdl terms, one for exchange rate (12 lags and 2^{nd}-order polynomial and constrained on both ends) and the other for foreign price (10 lags and 3^{rd}-order polynomial and constrained on both ends).

We note here that the PDL model regresses ΔLP_t on the derived variables, Z_{it}, as explained in section 3.1, and not on the current and lagged original dependent variables. The results for the specified PDL model are given in Table 6.1. All coefficients of the derived variables

	Coefficient	Std Error	$t - Statistic$	Probability
C	0.001845	0.001412	1.306334	0.1927
Z_{0t}	0.016049	0.002732	5.874671	0.0000
Z_{1t}	0.338080	0.079726	4.240548	0.0000
Z_{2t}	-0.077638	0.019406	-4.000666	0.0001
S.E. of regression	0.012878	Akaike info criterion		-5.850820
Sum squared resid	0.040962	Schwarz criterion		-5.794637
Log likelihood	738.2779	Hannan-Quinn criter.		-5.828210
F-statistic	13.85116	Durbin-Watson stat		1.890341
Prob(F-statistic)	0.000000			

Table 6.1: The estimated coefficients from the regression of ΔLP_t on the derived variables denoted as Z_{0t}, Z_{1t} and Z_{2t}.

are significant at the 1% level of significance and the Durbin-Watson statistic value of around

2 suggests that the residuals are not serially autocorrelated. Hence, the selected lag lengths and polynomial degrees provide a good fit, giving the estimation equation;

$$\Delta LP_t = 0.001845 + 0.016049Z_{0t} + 0.338080Z_{1t} - 0.077638Z_{2t}. \tag{6.1}$$

The coefficients of interest, β_i and γ_i are recovered by back substitution using the relationships $\beta_i = \sum_{h=0}^{p_1} a_h(i - \overline{c_1})^h$ and $\gamma_i = \sum_{h=0}^{p_2} b_h(i - \overline{c_2})^h$ (equations 3.2 and 3.3) respectively. They are given in Table 6.2.

Lag of ΔLE_t	Coefficient	Std Error
0	0.01490	0.00254
1	0.02751	0.00468
2	0.03783	0.00644
3	0.04585	0.00781
4	0.05159	0.00878
5	0.05503	0.00937
6	0.05617	0.00956
7	0.05503	0.00937
8	0.05159	0.00878
9	0.04585	0.00781
10	0.03783	0.00644
11	0.02751	0.00468
12	0.01490	0.00254
Sum of Lags	0.52160	
Lag of ΔLP^*_t	**Coefficient**	**Std Error**
0	0.26456	0.06159
1	0.39858	0.09133
2	0.42679	0.09603
3	0.37392	0.08310
4	0.26471	0.06192
5	0.12388	0.04845
6	0.02384	0.05844
7	0.15370	0.07876
8	0.24098	0.09205
9	0.26094	0.08828
10	0.18886	0.05988
Sum of Lags	0.98414	

Table 6.2: The coefficients of interest, β_i and γ_i for the repective fitted lag lengths.

The respective sum of lags for ΔLE_t and ΔLP_t^* reported in Table 6.2 have the interpretation of the long run effect of exchange rate changes and changes in foreign prices of goods on imports, assuming stationarity. Hence, this suggests that approximately 52% (coefficient of ΔLE_t) of exchange rate changes pass-through to South Africa's import prices.

6.2 Fitting the Johansen-type VECM

Figure 6.2 gives the time series plots of the logged series. They give the impression that

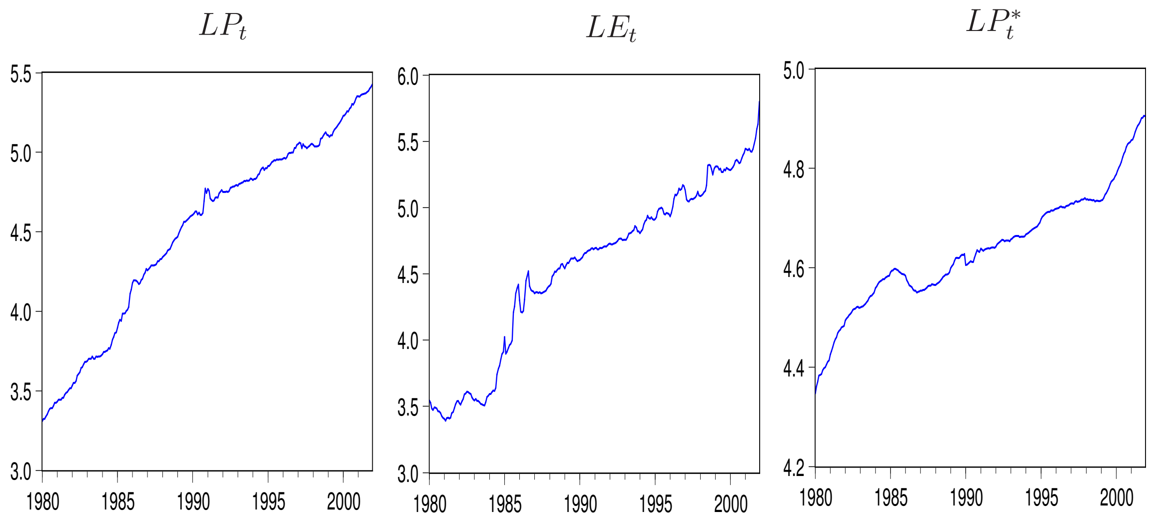


Figure 6.2: Time series plots of the logged series.

they all behave in a fashion characteristic of a random walk process plus drift. This is because, although not very pronounced, there is a non-decaying tendency for all the three series, supporting the possibility of a trend. We establish unit root properties of the data by carrying-out unit root tests.

6.2.1 Results of Unit Root Tests

We use standard Augmented Dickey-Fuller tests for unit roots described in section 2.6.4 to establish the integration order of the variables. This choice, as opposed to other Dickey-

Fuller tests has the advantage that it avoids imposing the restriction that all the three series can be adequately described by an AR (1) process. We adopt the automatic lag length selection for the unit root tests based on the Schwarz information criterion with an arbitrary maximum lag of 15. The probability values are the one-sided p-values of MacKinnon (1996). For each series, we included the constant and trend when testing for unit roots. If either the constant or trend is statistically insignificant, we drop it in the final test (No), otherwise we keep it (Yes). We report below a summary of the results for unit root tests of the lagged variables for both levels and first differences. The hypotheses to be tested are:

	LP_t	LE_t	LP_t^*	ΔLP_t	ΔLE_t	ΔLP_t^*
p-value	1.0000	0.5166	0.9997	0.0000	0.0000	0.0000
Constant	No	Yes	No	Yes	No	Yes
Trend term	No	Yes	No	Yes	No	Yes
Lag length	1	1	3	0	0	0

Table 6.3: Unit root test results for the levels and first differences of the logged series

H_0 : Variable has a unit root $Versus$ H_A : Variable has no unit root

For the levels, it follows from the p-values for each logged variable in Table 6.3, that we fail to reject the null of a unit root. On the other hand, we reject the null of a unit root for the first differences for all the three series. This shows that the logged series are all stationary after being differenced once, suggesting the series are all integrated of order one, denoted $I(1)$. Plots of the autocorrelation and partial autocorrelation functions for the three series in Appendix C, D and E also support this conclusion since they largely fall within the confidence bands.

6.2.2 Estimating and Analysing the Vector Autoregression (VAR)

Having established the integration order of the variables, we attempt to find important interrelationships among the variables if any, as opposed to fitting parsimonious models for short term forecasts which is the explicit aim of the Box - Jenkins approach. This is based on Sims (1980) criticisms of the incredible “identification restrictions” inherent in structural models in which he argued for VAR analysis as an alternative estimation procedure. His argument is that regressors are likely to be highly collinear, making t-tests on individual coefficients unreliable guides for paring down the model. Sims's methodology entails determining variables to be included in the VAR (according to the relevant economic model) and lag length selection. In our case, the relevant economic model for the long-run exchange rate pass-through is equation 1.9, indicating that all the variables need to be included in the VAR.

Concerning lag order selection of the VAR, we employed information criteria. The most widely used criteria are the Schwarz Bayesian and Akaike information criteria. The former imposes a harsher penalty than the latter thereby resulting in shorter lag length for the normally considered sample sizes. As a result, we select our VAR lag length on the basis of the Akaike information criterion. We give below the output from running an Eviews program which is given in Appendix *A*.

Lag	LogL	LR	FPE	AIC	SBC	HQ
0	508.7649	NA	4.1006	-3.890500	-3.849415	-3.873983
1	2422.101	3767.801	$1.78e-12$	-18.53924	-18.37490	-18.47317
2	2470.529	94.24883	$1.32e-12$	-18.84253	-18.55494^*	-18.72692^*
3	2482.481	22.98304*	$1.29e-12^*$	-18.86524^*	-18.45439	-18.70007
4	2490.435	15.11420	$1.30e-12$	-18.85720	-18.32309	-18.64248

Table 6.4: VAR lag length selection. * indicates lag order selected by the criterion, LR is the sequential modified LR test statistic (each test at 5 percent level), FPE is the Final prediction error, AIC is the Akaike information criterion, SBC is the Schwarz Bayesian information criterion and HQ is the Hannan-Quinn information criterion

It follows from Table 6.4 that AIC selects a lag order of 3, hence we fit a $VAR(3)$ model as shown in Table 6.5.

	LP^*_t	LE_t	LP_t
LP^*_{t-1}	0.990782	-0.293080	-0.052143
	(0.06183)	(0.15498)	(0.01460)
	[16.0241]	[-1.89113]	[-3.57206]
LP^*_{t-2}	0.029914	0.081039	0.055403
	(0.08793)	(0.22038)	(0.02076)
	[0.34022]	[0.36772]	[2.66896]
LP^*_{t-3}	-0.079427	0.208799	-0.005796
	(0.05897)	(0.14780)	(0.01392)
	[-1.34696]	[1.41271]	[-0.41636]
LE_{t-1}	0.054808	1.218263	0.001592
	(0.02616)	(0.06557)	(0.00618)
	[2.09500]	[18.5791]	[0.25776]
LE_{t-2}	0.047292	0.149691	-0.004790
	(0.04084)	(0.10238)	(0.00964)
	[1.15784]	[-1.46217]	[-0.49676]
LE_{t-3}	-0.055303	-0.095896	0.004719
	(0.02689)	(0.06741)	(0.00635)
	[-2.05638]	[-1.42264]	[0.74332]
LP_{t-1}	0.897853	-1.129792	1.355570
	(0.26010)	(0.65193)	(0.06141)
	[3.45197]	[-1.73301]	[22.0755]
LP_{t-2}	-1.014970	1.662900	-0.116198
	(0.44410)	(1.11311)	(0.10485)
	[-2.28546]	[1.49392]	[-1.10827]
LP_{t-3}	0.155085	-0.357340	-0.235411
	(0.25944)	(0.65026)	(0.06125)
	[0.59778]	[-0.54953]	[-3.84349]

Table 6.5: The fitted $VAR(3)$ model from the econometrics package, Eviews. The standard errors are in ( ) and t-statistics are in [ ]

The specified $VAR(3)$ in Table 6.5 is the equivalent form of the $VAR(p)$ model ($p = 3$) in equation 6.2.2, which we repeat here for easy reference.

$$\mathbf{Y_t} = \mathbf{\Phi D} + \mathbf{\Pi_1 Y_{t-1}} + ... + \mathbf{\Pi_p Y_{t-p}} + \mathbf{e_t}$$

The vectors are specified as follows; $\mathbf{Y_t} = [LP_t, LE_t, LP_t^*]^{'}$, $\mathbf{Y_{t-1}} = \left[LP_{t-1}, LE_{t-1}, LP_{t-1}^*\right]^{'}$, $\mathbf{Y_{t-2}} = \left[LP_{t-2}, LE_{t-2}, LP_{t-2}^*\right]^{'}$ and $\mathbf{Y_{t-3}} = \left[LP_{t-3}, LE_{t-3}, LP_{t-3}^*\right]^{'}$. The specified $VAR(3)$ is said to be stable and covariance stationary if the individual eigenvalues of the matrix of coefficients of lagged variables have modulus less than one. These eigenvalues are specified in Table 6.6.

Root	Modulus
0.998526	0.998526
0.976750	0.976750
0.868861	0.868861
0.702585	0.702585
0.442701 - 0.202376i	0.486765
0.442701 + 0.202376i	0.486765
-0.278483 - 0.171992i	0.327314
-0.278483 + 0.171992i	0.327314
-0.310542	0.310542

Table 6.6: Modulus of the individual eigenvalues of the matrix of coefficients of lagged variables.

Since none of the inverse roots lie outside the unit circle, the specified $VAR(3)$ model satisfies the stability and stationarity conditions.

Diagnostic checking, which is essentially a study of the residuals, is used to check for the validity of the fitted $VAR(3)$ model. In theory, we expect them to behave like white noise; otherwise they contain information which we would prefer to be captured in the fitted model. Thus, most importantly, the residuals must be serially uncorrelated though we will also look at tests for independence and normality. We consider here a test for serial correlation using the VAR Residual Serial Correlation Lagrange Multiplier (LM) tests as follows:

H_0 : No serial correlation at lag order h $Versus$ H_A : Serial correlation at lag order h

The results of the VAR Residual Serial Correlation LM tests are given in Table 6.7

Lags	LM-Stat	Probability.
1	15.22324	0.0850
2	26.38701	0.0018
3	6.385565	0.7008
4	13.98259	0.1229
5	16.00865	0.0667
6	15.90221	0.0690
7	8.168954	0.5172
8	13.00161	0.1625
9	28.33337	0.0008
10	9.151093	0.4234
11	7.083836	0.6284
12	11.43545	0.2470

Table 6.7: LM-Statistics for the VAR residual serial correlation tests. The Probabilities are from a chi-square with 9 degrees of freedom.

Thus, apart from lags 2 and 9, we fail to reject the null hypothesis at the 5% level of significance. As a result, we conclude that the residuals are largely uncorrelated.

The test for statistical independence of residuals can be performed by looking at the autocorrelation plots of the residuals. For independence, the residual autocorrelations must lie within the confidence limits. Figure 6.3 gives the plots of the residual autocorrelations. The subscript t in the three series is dropped and LFP represents LP^* (which is an illegal or reserved name in the Eviews software). As can be seen from Figure 6.3, a few of the residual autocorrelations are outside the confidence limits (outliers) though the majority lie within the confidence limits. Hence, we conclude that the residuals are independent to a large extent.

Tests for multivariate normality of residuals are violated more often in financial data. Several orthogonalisation methods that can be used are available but we adopt the Cholesky of the covariance matrix, as in the Lutkepohl test. The hypotheses to be tested are:

H_0 : Residuals are multivariate normal $Versus$ H_A : Residuals are not multivariate normal

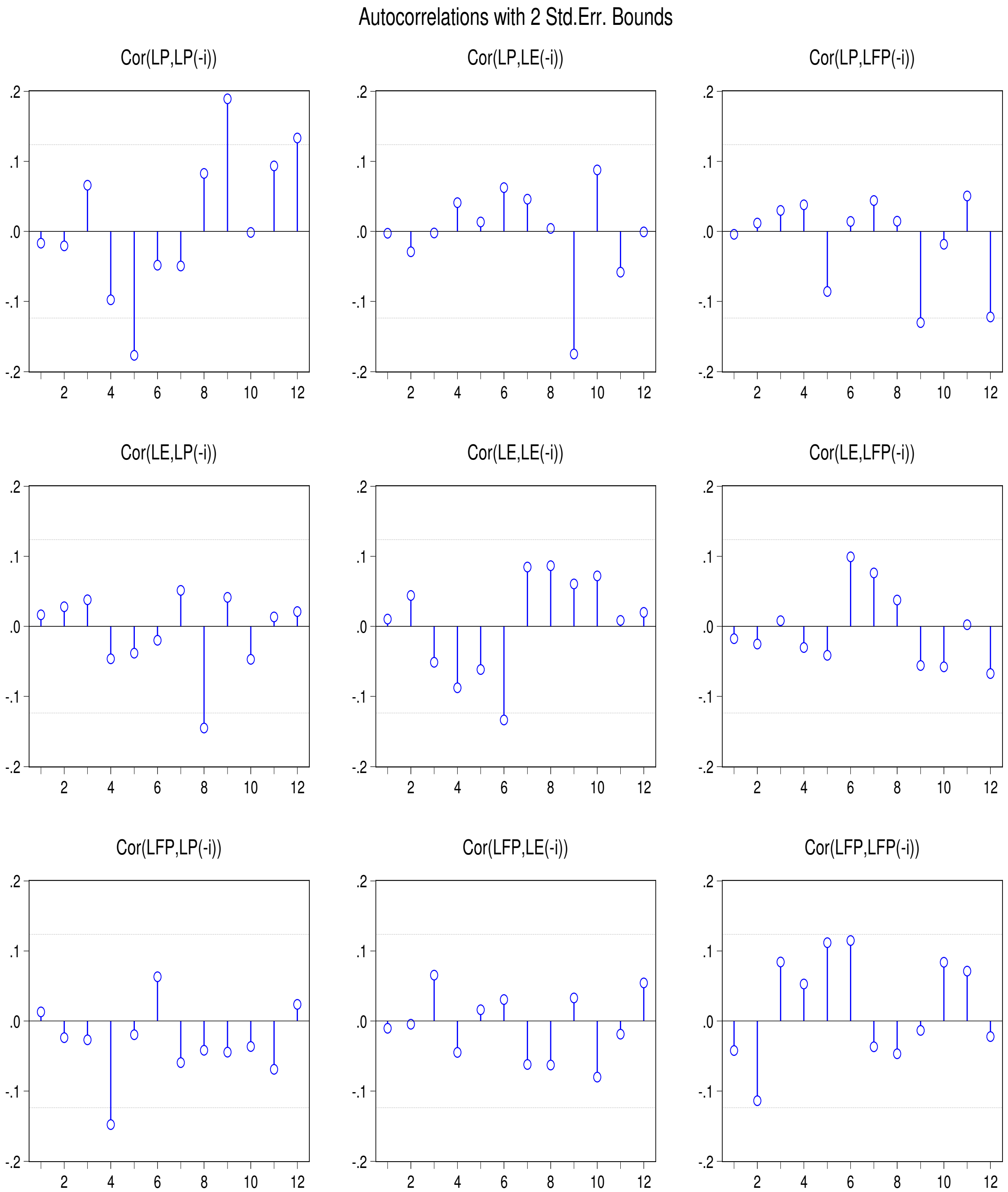


Figure 6.3: Residual autocorrelation plots with 2 standard error bounds.

Results for multivariate normality are given in Table 6.8. Looking at the probability values

Component	Skewness	Chi-sq	df	Probability.
1	1.471054	94.13400	1	0.0000
2	0.792386	27.31255	1	0.0000
3	-1.849904	148.8633	1	0.0000
Joint		270.3099	3	0.0000
Component	Kurtosis	Chi-sq	df	Probability.
1	10.78513	659.1141	1	0.0000
2	13.18990	1129.195	1	0.0000
3	20.67862	3398.803	1	0.0000
Joint		5187.112	3	0.0000

Table 6.8: Multivariate normality tests for the residauls.

in Table 6.8, it can be seen that the residuals are not normally distributed, which is often the case with financial data.

Finally, we expect the time series plots of residuals to behave like white noise, exhibiting a zero mean and a stationary variance. It follows from figure 6.4 that the residuals do behave

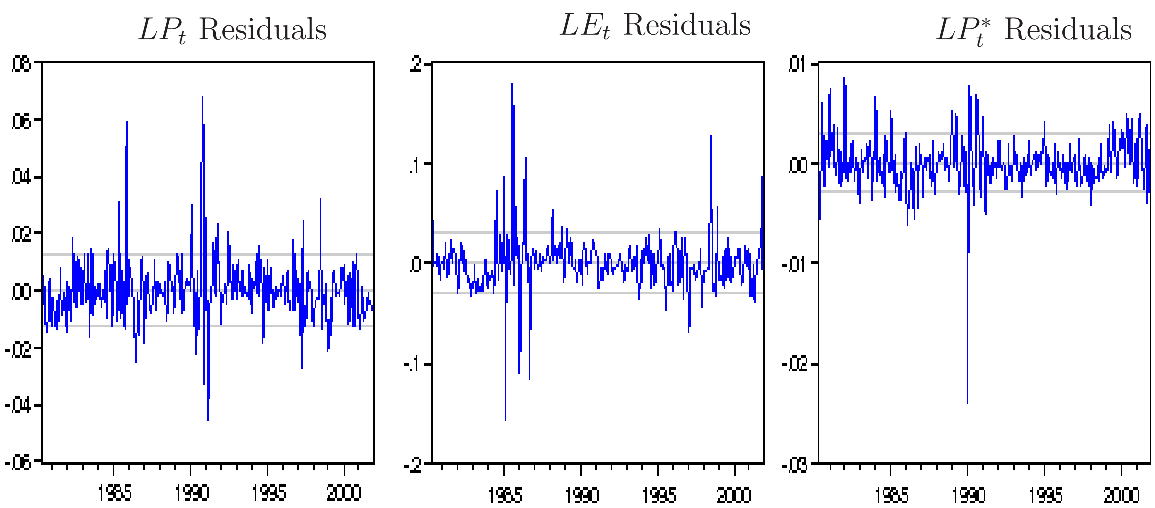


Figure 6.4: Residual time series plots.

like white noise, even though there are some volatile periods. Thus, we conclude that the diagnostic testing results are to a large extent statistically satisfactory; meaning the fitted VAR (3) model is statistically adequate.

6.2.3 Finding the Number of Co-integrating Vectors

The variables in the estimated $VAR(3)$ are all integrated of order one. Thus, if they are co-integrated, then their linear combination should have a lower order of integration. The $VAR(3)$ process can be reparameterised into a vector error correction model (VECM), capturing the transitional dynamics of the system to the long-run equilibrium suggested by economic theory as explained by equation 3.13. Of particular importance is the matrix $\mathbf{\Pi}$ since the Johansen methodology provides inference on the number of non-zero eigenvalues of $\mathbf{\Pi}$.

To estimate the long-run exchange rate pass-through relationship, the Johansen procedure uses two unrestricted co-integration rank tests, namely the Trace and Maximum Eigenvalue tests. Results of the two tests are summarised in Table 6.9.

Hypothesised No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Probability.
$None^*$	0.101392	42.08272	29.79707	0.0012
At most 1	0.052495	14.17963	15.49471	0.0781
At most 2	0.000405	0.105712	3.841466	0.7451
Hypothesised No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Probability.
$None^*$	0.101392	27.90309	21.13162	0.0048
At most 1	0.052495	14.07391	14.26460	0.0535
At most 2	0.000405	0.105712	3.841466	0.7451

Table 6.9: Both the Trace and Maximum-eigenvalue tests indicate one co-integrating equation at the 0.05 level. * denotes rejection of the hypothesis at the 0.05 level and the probability values use the formulae of MacKinnon-Haug-Michelis (1999).

The results reported in Table 6.9 are for the co-integration tests, conducted on the basis of the estimated VAR (3) process. Both tests select a single co-integration relationship between the variables. We specify the VECM with one co-integrating vector in Table 6.10.

Error Correction:	ΔLP_t	ΔLE_t	ΔLP_t^*
CointEq1	-0.054819	-0.033819	-0.002088
	(0.01082)	(0.02773)	(0.00255)
	[-5.06867]	[1.21950]	[-0.81819]
ΔLP_{t-1}	0.050428	-0.280048	-0.049292
	(0.05860)	(0.15027)	(0.01383)
	[0.86050]	[-1.86368]	[-3.56398]
ΔLP_{t-2}	0.085243	-0.150359	0.007082
	(0.05843)	(0.14982)	(0.01379)
	[1.45892]	[-1.00359]	[0.51359]
ΔLE_{t-1}	0.012889	0.292607	0.000781
	(0.02611)	(0.06695)	(0.00616)
	[0.49360]	[4.37022]	[0.12668]
ΔLE_{t-2}	0.058740	0.128081	-0.004396
	(0.02628)	(0.06740)	(0.00620)
	[2.23475]	[1.90036]	[-0.70859]
ΔLP_{t-1}^*	0.901274	-0.895138	0.359748
	(0.25836)	(0.66249)	(0.06098)
	[3.48838]	[-1.35118]	[5.89978]
ΔLP_{t-2}^*	-0.118363	0.725452	0.243369
	(0.25529)	(0.65460)	(0.06025)
	[-0.46364]	[1.10823]	[4.03926]
C	0.004782	0.009283	0.001146
	(0.00115)	(0.00295)	(0.00027)
	[4.16315]	[3.15138]	[4.22727]

	CointEq1
LP_{t-1}	1.000000
LE_{t-1}	-0.848073
	(0.05681)
	[-14,9294]
LP_{t-1}^*	-0.342729
	(0.31873)
	[-1.07529]
C	0.936344

Table 6.10: Vector Error Correction Estimates. The standard errors are in ( ) and t-statistics are in [ ].

The VECM representation of the specified $VAR(3)$ in Table 6.10 is the equivalent form of the VECM in equation 5.1, which we repeat here for easy reference.

$$\mathbf{\Delta Y_t} = \mathbf{\Phi D} + \alpha\beta^{'}\mathbf{Y_{t-1}} + \mathbf{\Gamma(1)\Delta Y_{t-1}} + ... + \mathbf{\Gamma(p-1)\Delta Y_{t-p+1}} + \mathbf{e_t}$$

The vector, $\beta = [1, -0.848073, -0.342729]^{'}$ is the unrestricted co-integration relation and $\alpha = [-0.054819, -0.033819, -0.002088]^{'}$ is the vector of the speed of adjustment coefficients.

On the basis of a single co-integrating vector, an economically meaningful test to consider is that the pass-through coefficients from exchange rate and foreign price changes have the same magnitude. This transforms to testing the restriction that $\beta_1 = \beta_2$ in equation 1.9. Hence, the hypotheses to be tested are:

H_0 : Restrictions are binding $Versus$ H_A : Restrictions are not binding.

Results for the test of co-integrating restrictions are given in Table 6.11.

Hypothesised No. of CE(s)	Restricted Log-likelihood	LR Statistic	Degrees of Freedom	Probability.
1	2484.691	0.905268	1	0.341373
2	2492.181	NA	NA	NA
Restricted Co-integrating Coefficients				
LP_t	LE_t	LP_t^*		
1.000000	-0.774536	-0.774536		
(0.00000)	(0.01723)	(0.01723)		
Adjustment Coefficients				
ΔLP_t	-0.059234			
	(0.01153)			
ΔLE_t	0.009026			
	(0.02968)			
ΔLP_t^*	-0.002655			
	(0.00272)			

Table 6.11: Tests of co-integrating restrictions. The imposed restrictions are $\beta_1 = \beta_2$ to ensure pass-through coefficients from exchange rate and foreign price changes are equal and normalising by making the coefficient of LP_t one. NA indicates that restrictions are not binding and the numbers in parentheses are standard errors.

It follows from Table 6.11 that we fail to reject the null hypothesis and conclude that the restrictions are binding for one co-integrating vector. Imposing this restriction and normalising the restricted co-integrating coefficients on the coefficient of the domestic price of the import variable results in the estimated long-run pass-through relationship:

$$L\hat{P}_t = 0.774536L\hat{E}_t + 0.774536L\hat{P}_t^* \qquad (6.2)$$

The graphical representation of the co-integrating relation is shown in Figure 6.5. It fol-

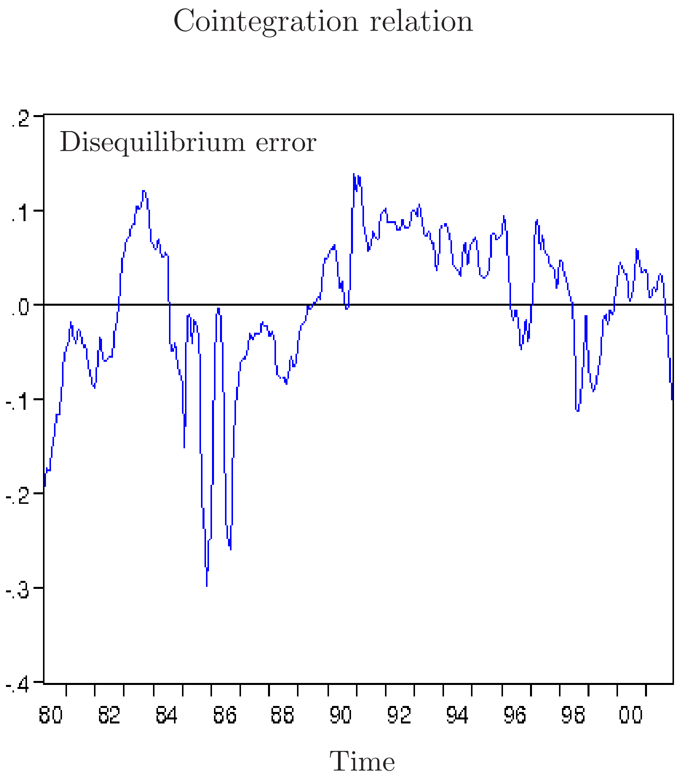


Figure 6.5: The unrestricted co-integrating relation for the sample January 1980 to December 2001 of the South Africa data. The equilibrium error rarely drifts far from zero and crosses the zero line quite often showing that the three series are co-integrated.

lows from equation 6.2 that about 77% of exchange rate changes pass-through to South Africa's import prices in the long-run. This is also the long-run exchange rate pass-through percentage obtained by Rangasamy and Farrell (2002) using the same data set. Their long-relationship, based also on the $VAR(3)$ model is given by;

$$LP_t = 0.776LE_t + 0.776LP_t^*. \tag{6.3}$$

6.3 Comparison of the Models

We use information criteria to compare the performance of the two models based on the sample January 1980 to December 2001. The results are reported in Table 6.12. It is

	AIC	SBC	S.E of Equation	Sum squared resid
PDL	-5.850820	-5.794637	0.012878	0.040962
VECM				
ΔLP_t	-5.949907	-5.840650	0.012168	0.037457
ΔLE_t	-4.066648	-3.957391	0.031200	0.246275
ΔLP_t^*	-8.837669	-8.728411	0.002872	0.002086

Table 6.12: Results on information criteria and standard errors for the two models. Note that VECM reports information criteria results for each of the three series in the dynamic system of equations.

interesting to note that, although the three series were estimated simultaneously, the VECM reports different information criteria results for each. This is presumably because, since the VECM is a system of equations, then each equation in the system is selected according to its own information criteria. Since we are interested in pass-through into import prices, we only consider information criteria values corresponding to the import price equation in the VECM for comparison purposes. As can be seen from the information criteria results and standard errors in Table 6.12, there is not much to choose between the two models. This indicates that on the basis of information criteria, the two models generally perfom roughly equally.

6.4 A Monte Carlo Simulation Study

Since the true model is unknown, a simulation study is used to generate data sets for model fitting in order to compare the methodologies. A possible criterion for comparing the models in this case would be the the stability of parameter estimates.

However, care must be taken when choosing the model(s) from which to simulate the data. In particular, the model should be applicable to estimating exchange rate pass-through over and above being mathematically related to the PDL and VECM, the methodologies we are comparing. We make an assumption that the pass-through estimate from the model(s) used to simulate the data will be naturally treated as the true pass-through. This assumption is reasonable because we expect the model that generates the data to yield a better estimate than models that did not generate the data. Under this assumption, we determine which of the PDL and VECM pass-through estimates best approximates the true pass-through.

6.4.1 ARDL Models and Long-run Multipliers

According to Hassler and Wolters (2005), equation 3.14 is ideal for estimation, but a transformation is required to obtain an economic interpretation of its parameters. To obtain dynamic stability, Hassler and Wolters (2005) maintain $\pi(z) = 0$ implies that $|z| > 1$ for $z \in \mathbb{C}$, a condition ensuring the existence of an absolutely summable infinite expansion of the inverted polynomial $\pi^{-1}(L)$ as:

$$\begin{aligned} \pi^{-1}(L) &= \frac{1}{\pi(L)} \\ &= \sum_{j=0}^{\infty} \pi_j^* L^j \end{aligned} \tag{6.4}$$

where $\sum_{j=0}^{\infty} |\pi_j^*|$ is finite. It follows from equation 3.15 that invertibility of $\pi(L)$ results in the representation

$$LP_t = \frac{\mathbf{c}'(\mathbf{L})}{\pi(L)} \mathbf{X_t} + e_t \tag{6.5}$$

where $\pi(L)e_t = \epsilon_t$ and e_t has a stable autoregressive structure of order p. Thus, expanding $\pi^{-1}(L)$ results in an infinite distributed lag representation

$$\begin{aligned} LP_t &= \left(\sum_{j=0}^{\infty} \pi_j^* L^j\right)\left(\sum_{j=0}^{\infty} \mathbf{c_j L^j}\right)' \mathbf{X_t} + \mathbf{e_t} \\ &= \sum_{j=0}^{\infty} \mathbf{b_j'X_{t-j}} + e_t \end{aligned} \tag{6.6}$$

where $\mathbf{b_j}$ are the vectors of dynamic multipliers derived by the method of undetermined coefficients with the vector of long-run multipliers computed from

$$\beta = \sum_{j=0}^{\infty} \mathbf{b_j}. \tag{6.7}$$

This shows that ARDL models are applicable to estimating long-run exchange rate pass-through.

Following our discussion of the models in Chapter 3 and their relationships, we chose to simulate data from the ARDL model since it is the most general. To simulate data from model 3.14, we need to specify LE_t and LP_t^*. These two series however are not well described by simple autoregressive models, leaving us with no known theory for calculating pass-through when models for these series are incorporated into the ARDL model. However, according to Anaman (2004), the ARDL model is a vector autoregressive (VAR) model. Fabozzi *et al* (2005) also describe a family of ARDL models as an extension of pure VAR models. They argue that the ARDL model is nothing but the coupling of a regression model and a VAR model as follows:

$$LP_t = \alpha_0 + \pi_1 LP_{t-1} + ... + \pi_p LP_{t-p} + \beta_\mathbf{0}\mathbf{X_t} + ... + \beta_\mathbf{s}\mathbf{X_{t-s}} + \eta_\mathbf{t}. \tag{6.8}$$

$$\mathbf{X_t} = \mathbf{A_1X_{t-1}} + \mathbf{A_2X_{t-2}} + ... + \mathbf{A_qX_{t-q}} + \epsilon_\mathbf{t}.$$

Thus, in the ARDL model in equation 6.8, LP_t is regressed over its past values and over past values of $\mathbf{X_t}$ which is distributed according to a $VAR(p)$ model. The ARDL model is transformed into a VAR model to give

$$\begin{pmatrix} LP_t \\ LP_(t-1) \\ . \\ LP_{t-p+1} \\ LP_{t-p} \\ \mathbf{X_t} \\ \mathbf{X_{t-1}} \\ . \\ \mathbf{X_{t-q}} \end{pmatrix} = \begin{pmatrix} \pi_1 & \pi_2 & . & \pi_{p-1} & \pi_p & \beta_0 & \beta_1 & . & \beta_s & . & 0 & 0 \\ 1 & 0 & . & 0 & 0 & 0 & 0 & . & 0 & . & 0 & 0 \\ . & . & . & . & . & . & . & . & . & . & . & . \\ 0 & 0 & . & 1 & 0 & 0 & 0 & . & 0 & . & 0 & 0 \\ 0 & 0 & . & 0 & 1 & 0 & 0 & . & 0 & . & 0 & 0 \\ 0 & 0 & . & 0 & 0 & 0 & \mathbf{A_1} & . & \mathbf{A_s} & . & \mathbf{A_{q-1}} & \mathbf{A_q} \\ 0 & 0 & . & 0 & 0 & 0 & 1 & . & 0 & . & 0 & 0 \\ . & . & . & . & . & . & . & . & . & . & . & . \\ 0 & 0 & . & 0 & 0 & 0 & 0 & . & 0 & . & 0 & 0 \\ 0 & 0 & . & 0 & 0 & 0 & 0 & . & 0 & . & 1 & 0 \end{pmatrix} \begin{pmatrix} LP_{t-1} \\ LP_{t-2} \\ . \\ LP_{t-p+1} \\ LP_{t-p} \\ \mathbf{X_t} \\ \mathbf{X_{t-1}} \\ . \\ \mathbf{X_{t-s}} \\ . \\ \mathbf{X_{t-q}} \\ \mathbf{X_{t-q-1}} \end{pmatrix}$$

$$+ \begin{pmatrix} \alpha_0 \\ 0 \\ . \\ 0 \\ 0 \\ 0 \\ 0 \\ . \\ 0 \end{pmatrix} + \begin{pmatrix} \eta_t \\ 0 \\ . \\ 0 \\ \epsilon_t \\ 0 \\ 0 \\ . \\ 0 \end{pmatrix} \tag{6.9}$$

Following the transformation of the ARDL model into a VAR, Fabozzi *et al* (2005) argue that the estimation of the ARDL model can be done with methods used for VAR models. Based on the transformation of an ARDL model into a VAR, we simulate data from the fitted $VAR(3)$ model using the values in the first three time points (1980 to 1982) since the maximum lag of a $VAR(3)$ is 3 as the initial values and the estimated variance-covariance matrix of the fitted VAR residuals as the random component. The simulations were run using the statistical package R, and the code is given in Appendix B. We give below time series plots of one of the simulated series as a check of how close the simulated data are to the actual data in Figure 6.2. It can be seen from Figures 6.6 that the simulated data

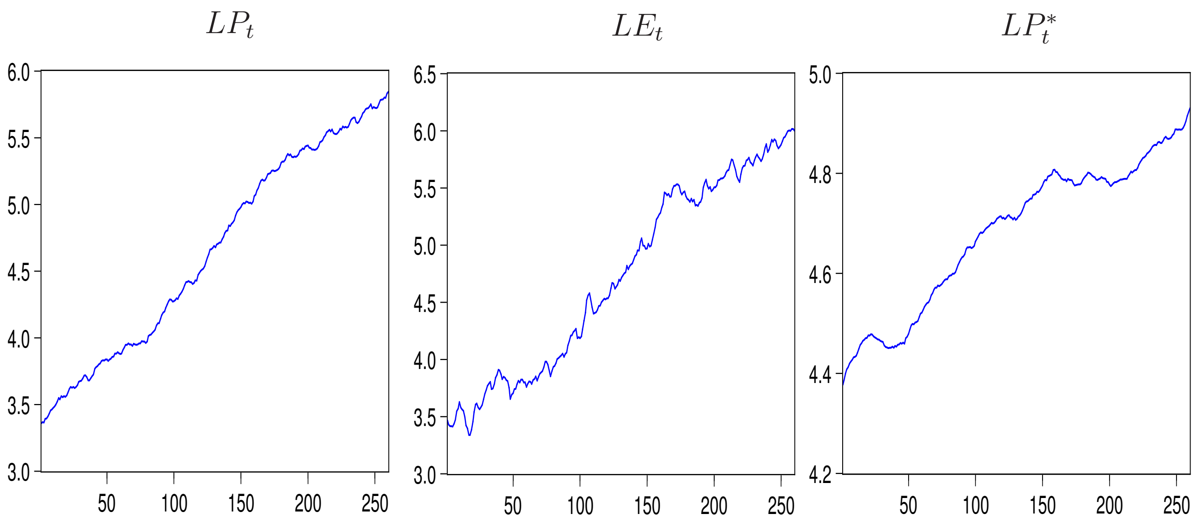


Figure 6.6: Time series plots of the one of the simulated logged series.

provides a good approximation to the actual data.

Treating the pass-through estimate from the model used to simulate data as the true pass-through allows us to calculate the bias of the estimates from our two models of interest, the PDL and the VECM and provides a basis for comparing them. We adopt here two approaches to estimating true pass-through namely a purely statistical approach (derived directly from the fitted $VAR(3)$) and a direct fitting of the ARDL model to the actual data using the cointegration approach by Pesaran *et al* (2001). The latter is a more econometric approach than the former.

6.4.2 Statistical Approach to Calculating True Pass-Through

Recall that the the reduced form VAR errors in equation 3.8 are normally distributed with mean zero and variance covariance matrix, Σ. It follows then that the vector $\mathbf{Y_t} = [LP_t, LE_t, LP_t^*]'$ follows a multivariate normal distribution. Thus, we can find the distribution of LP_t conditional on $\mathbf{X_t}$, with the subscript removed for simplicity (recall $\mathbf{X_t}$=$[LE_t, LP_t^*]'$) using the theorem which states that:

"*If*

$$\begin{pmatrix} LP \\ \mathbf{X} \end{pmatrix} \sim N_{k+1}\left[\begin{pmatrix} \mu_{LP} \\ \mu_{\mathbf{X}} \end{pmatrix}, \begin{pmatrix} \Sigma_{LPLP} & \Sigma_{LP\mathbf{X}} \\ \Sigma_{\mathbf{X}LP} & \Sigma_{\mathbf{XX}} \end{pmatrix}\right]$$

where $LP \in \mathbb{R}$, $\mathbf{X} \in \mathbb{R}^k$ *and* $\Sigma_{\mathbf{XX}}$ *is nonsingular (variance covariance matrix), then conditional on* $\mathbf{X}$, LP *follows a normal distribution with mean* $E(LP|\mathbf{X}) = \beta_{\mathbf{0}} + \beta'\mathbf{X}$ *for* ($\beta = [\beta_{\mathbf{1}}, \beta_{\mathbf{2}}]'$) *where* $\beta = \mathbf{\Sigma_{XX}^{-1}\Sigma_{XLP}}$ *and* $\beta_0 = \mu_{LP} - \beta'\mu_X$ *and conditional variance* $Var((LP|\mathbf{X}) = \mathbf{\Sigma_{LPLP} - \Sigma_{LPX}\Sigma_{XX}^{-1}\Sigma_{XLP}}$ *(Bierens, 2004)*"

The result presented in the theorem is the basis for linear regression analysis. It is applicable to equation 1.9, where the economic varible, LP_t is influenced by other economic variables, LE_t and LP_t^*. Such a relationship is often modeled linearly by

$$LP_t = \beta_0 + \beta'\mathbf{X_t} + U_t \tag{6.10}$$

where U_t is an error term assumed to be independent of $\mathbf{X_t}$ (for ordinary least squares assumptions to hold) and is normally distributed with mean zero and variance σ^2. Thus, according to the theorem, a linear relation between $\mathbf{X_t}$ and LP_t, as in equation 6.10, exists provided $\mathbf{X_t}$ and LP_t are jointly normally distributed. To solve for the parameters β_0 and β in *R*, we show the variance-covariance matrix of the shorter data set in table form (Table 6.13). The low covariance value of 0.06768567 between LE_t and LP_t^* means the regressors are not highly correlated, and so the components of the vector β can be estimated using the ordinary least squares method. The matrix of interest, $\Sigma_{\mathbf{XX}}$ was easily extracted from the variance-covariance matrix, denoted here by `cov` in *R* using the command `rbind(cov[2:3,2:3])` and its inverse was also obtained in *R* using the command `solve(`Σ_{XX}`)` to give the inverse

	LP_t	LE_t	LP_t^*
LP_t	0.3616020	0.37946317	0.06494680
LE_t	0.3794632	0.40660309	0.06768567
LP_t^*	0.0649468	0.06768567	0.01320867

Table 6.13: The variance-covariance matrix of the sample January 1980 to December 2001 of the South Africa data.

matrix

$$\begin{pmatrix} 16.73389 & -85.75010 \\ -85.75010 & 515.12020 \end{pmatrix}$$

In the same way, the vector, $\Sigma_{\mathbf{X}LP_t}$ was obtained in R using the command `t(rbind(cov[2:3,2]))`. Hence, the vector of regression coefficients, β is the product of the inverse matrix and the vector Σ_{XY} given by

$$\beta = \begin{pmatrix} 1.000000e+00 \\ -3.344547e-15 \end{pmatrix} \tag{6.11}$$

On the basis of this statistical approach, exchange rate changes are fully passed through to South Africa's import prices in the long-run for the actual shorter data set.

6.4.3 Econometric Approach to Calculating True Pass-Through

Following the suggestion for cointegration analysis by Pesaran and Shin (1998), as summarised in Hassler and Wolters (2005), the ARDL model in equation 3.14 can be re-parameterised by re-arranging the $\mathbf{X's}$ to give

$$LP_t = \alpha_0 + \sum_{i=1}^{p} \pi_i LP_{t-i} + \pi(1)\beta' \mathbf{X_t} - \sum_{i=0}^{q-1} \left(\sum_{j=i+1}^{q} \mathbf{c_j} \right)' + \mathbf{\Delta X_{t-i}} + \epsilon_t. \tag{6.12}$$

It follows from equation 6.12 that LP_t is related to its own past, contemporaneous $\mathbf{X_t}$ and differences $\mathbf{\Delta X_{t-i}}$. Using the result in Hassler and Wolters (2005) that

$$\sum_{i=1}^{p} \pi_i LP_{t-i} - LP_{t-1} = -\pi(1) LP_{t-1} - \sum_{i=1}^{p-1} \left(\sum_{j=i+1}^{p} \pi_{\mathbf{j}} \right) \mathbf{\Delta} LP_{t-i} + \epsilon_t. \tag{6.13}$$

and $\mathbf{X_t} = \mathbf{X_{t-1}} + \mathbf{\Delta X_t}$, equation 6.12 yields the error correction representation

$$\begin{aligned} \mathbf{\Delta} LP_t &= -\pi(1)(LP_{t-1} - \beta^{'}\mathbf{X_{t-1}}) - \sum_{i=1}^{p-1}\left(\sum_{j=i+1}^{p}\pi_j\right)\mathbf{\Delta} LP_{t-i} \\ &+ \left(\pi_1(1)\beta - \sum_{j=1}^{q}\mathbf{c_j}\right)^{'}\mathbf{\Delta X_t} - \sum_{i=1}^{q-1}\left(\sum_{j=i+1}^{q}\mathbf{c_j}\right)^{'} + \mathbf{\Delta X_{t-i}} + \epsilon_t \end{aligned} \tag{6.14}$$

where the interpretation is based on the long-run equilibrium relation, ($LP_t = \beta^{'}\mathbf{X_{t-1}}$) in which the error correction mechanism is the adjustment of LP_t through $\pi(1)$ to deviations from equilibrium in the previous period, denoted ($LP_{t-1} - \beta^{'}\mathbf{X_{t-1}}$). Often, equation 6.14 is rewritten as

$$\mathbf{\Delta} LP_t = \pi LP_{t-1} + \mathbf{c}^{'}\mathbf{X_{t-1}} + \sum_{i=1}^{p-1} a_i \mathbf{\Delta} LP_{t-i} + \sum_{i=0}^{q-1}\mathbf{b_i^{'}}\mathbf{\Delta X_{t-i}} + \epsilon_\mathbf{t} \tag{6.15}$$

where $\pi = -\pi(1)$ and $\mathbf{c} = -\pi\beta$ (Hassler and Wolters, 2005). The ARDL co-integration approach builds on the error correction equation 6.15 to test for co-integration and derive the long-run equilibrium relationship and the short-run adjustments coefficients.

According to Pesaran and Pesaran (1997), estimation of the long-run coefficients within an autoregressive distributed lag framework is in two steps. They are (i) bounds tests for co-integration and (ii) estimation and analysis of the ARDL model.

6.4.4 Bounds Tests for Co-integration

The first step tests the existence of a long-run relationship among variables (co-integration) using an $F-$test for the joint significance of the coefficients of the lagged variables, called the "bounds testing procedure". It uses two asymptotic critical values where the lower one, denoted by L_c assumes $I(0)$ regressors and the upper value, denoted by U_c assumes $I(1)$ regressors. The hypotheses to be tested are:

H_0 : Variables are not co-integrated $Versus$ H_A : Variables are co-integrated

The decision to reject or accept the null hypothesis can be reached using the following rules:

(1) If $F-$statistic $> U_c$, reject H_0.

(2) If $F-$statistic $< L_c$, accept H_0.

(3) If $L_c < F-$statistic $< U_c$, the result is inconclusive.

However, probability values can also be used to make these decisions. The bounds tests procedure is to calculate $F-$statistics when each of the variables under consideration is considered as a dependent variable. We denote the test which normalises on LP_t say by $F_{LP_t}(LP_t'|LE_t, LP_t^*)$. Table 6.14 gives a summary of the co-integration testing results. Thus,

Dependent variable	SBC lags	$F-$statistic	Probability	Outcome
$F_{LP_t}(LP_t\|LE_t, LP_t^*)$	1	189076.2	0.0000	Co-integration
$F_{LE_t}(LE_t\|LP_t, LP_t^*)$	2	26483.8	0.0000	Co-integration
$F_{LP_t^*}(LP_t^*\|LP_t, LE_t)$	4	49808.3	0.0000	Co-integration

Table 6.14: Results from bounds tests for co-integration within an autoregressive distributed lag framework.

using the probability values, we reject the null hypothesis of no cointegration among the variables when the regressions are normalised on any of the variables. However, based on the LOP, we use LP_t as the dependent variable.

6.4.5 Estimation and Analysis of the Long-run and Short-run Elasticities

According to Pesaran and Shin (1998), the SBC is generally prefered to other criteria for estimating ARDL models because it gives more parsimonious specifications. We applied the ARDL cointegration approach in Microfit 4.0 and the resulting ARDL model is summarised in Table 6.15.

It follows from Table 6.15 that all the coefficients of the regressors, apart from that of the constant, are significant at the 5 percent level of significance. The high R-Squared value of 0.99955 also suggests good fit which is also supported by the time series plot of actual and fitted values in Figure 6.7. Since the $F-$statistic is very high, the long-run relationship among the variables can be determined in the first step, otherwise the error correction version of the ARDL model would have been used. The long-run coefficients and their asymptotic standard errors are given in Table 6.16. Thus the more econometric approach shows, from Table 6.16,

Regressor	Coefficient	Standard Error	T-Ratio	Probability
LP_{t-1}	0.93204	0.098026	95.0800	0.0000
LE_t	0.051790	0.084435	6.1338	0.0000
LP_t^*	0.06210	0.019960	2.8161	0.005
Constant	-0.18219	0.076972	-2.3669	0.019
R-Squared	0.99955	R-Bar-Squared	0.99954	
S.E of Regression	0.012555	F(3,248)	189076.2	0.0000
Residual Sum of Squares	0.040350	Log-likelihood	771.2858	
AIC	767.2858	SBC	760.1644	
DW-statistic	1.8265			

Table 6.15: Autoregressive Distributed Lag estimates for the ARDL(1,0,0) model selected based on the Schwarz Bayesian Criterion.

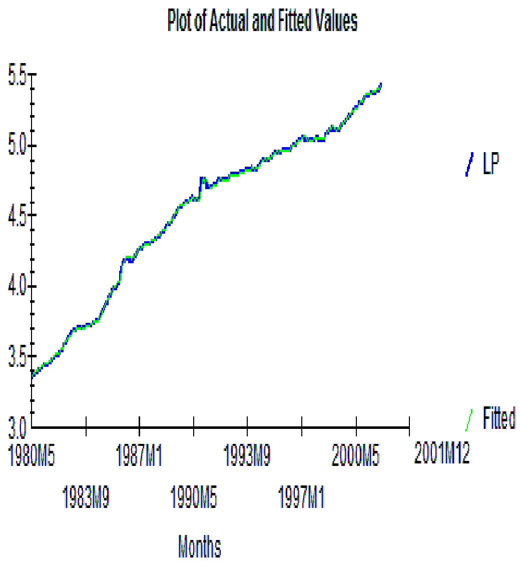


Figure 6.7: Time series plots of the actual and fitted values for the logged series of the domestic price of imports, LP_t.

that about 76% of exchange rate changes are passed through to South Africa's import prices for the actual shorter data set. The short-run adjustment coefficients are obtained from the error correction version of the ARDL model. They are reported in Table 6.17. The error correction term indicates the speed of adjustment to restore equilibrium in the dynamic model. In theory, the error correction model (ECM) coefficient should have a statistically significant negative coefficient. It shows how quickly variables converge to equilibrium. The

Regressor	Coefficient	Standard Error	T-Ratio	Probability
LE_t	0.76202	0.047727	15.9661	0.0000
LP_t^*	0.82706	0.26981	3.0653	0.002
Constant	-2.6806	1.0556	-2.3393	0.012

Table 6.16: Estimated long-run coefficients using the ARDL approach based on the ARDL(1,0,0) model selected by the Schwarz Bayesian Criterion.

Regressor	Coefficient	Standard Error	T-Ratio	Probability
ΔLE_t	0.051790	0.0084435	6.13338	0.0000
ΔLP_t^*	0.056210	0.019960	2.8161	0.005
$\Delta Constant$	-0.18219	0.076972	-2.3669	0.019
ECM_{t-1}	-0.067964	0.0098026	-6.9333	0.0000
R-Squared	0.165663	R-Bar-Squared	0.15589	
S.E of Regression	0.012555	F(3,248)	16.9444	0.0000
Residual Sum of Squares	0.040350	Log-likelihood	771.2858	
AIC	767.2868	SBC	760.1644	
DW-statistic	1.8265			

Table 6.17: Error correction representation for the selected ARDL(1,0,0) model based on the Schwarz Bayesian Criterion. R-squared measure refers to the dependent variable ΔLP_t and in cases where the error correction model is highly restricted, it could become negative.

ECM coefficient in Table 6.17 has the expected sign and is highly significant, confirming the existance of a stable long-run relationship. Hence, this supports the existance of the co-integration relationship among the variables. The ECM_{t-1} has a coefficient of -0.067964, which implies that approximately 6.8% of the disequilibria from the previous year's shock converges back to the long-run equilibrium in the current year. This finding shows that the speed of adjustment is very low and is consistent with reviewed literature which holds that partial pass-through takes a number of lags to occur.

6.5 ARDL-ECM Diagnostic and Stability Tests

We check the validity of the fitted ARDL model using diagnostic testing. In particular we analyse the time series plot of the residuals to establish if they behave like white noise, test for residual serial autocorrelation using the Durbin-Watson test and consider histogram plot of the residuals as a test for normality.

The time series plot of the residuals for the shorter data set is given in Figure 6.8. It follows

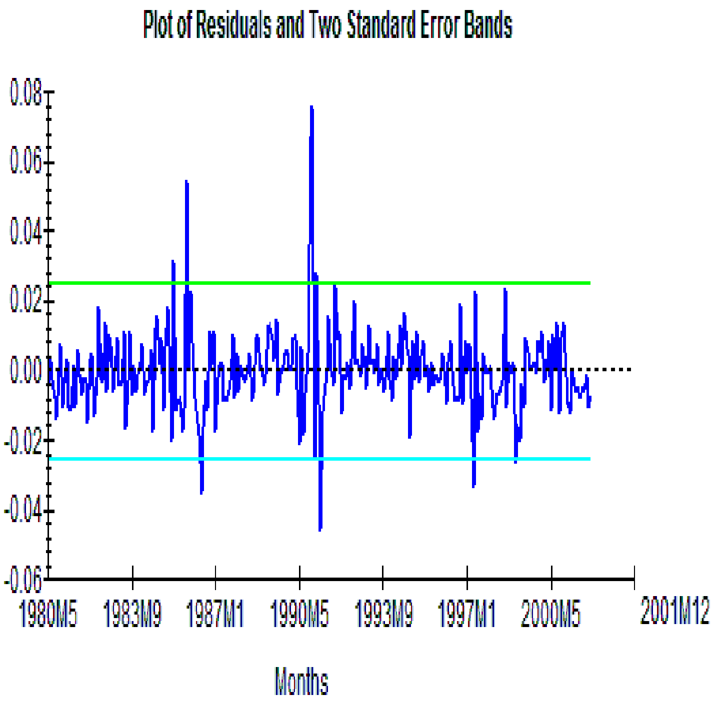


Figure 6.8: Residual time series plot.

from Figure 6.8 that the residuals largely behave like white noise although there are a few residuals outside the standard error bands. The Durbin-Watson statistic, d is approximated by

$$d \approx 2(1 - \hat{\rho}) \tag{6.16}$$

Since $-1 \leq \hat{\rho} \leq 1$, it is obvious from equation 6.16 that $0 \leq d \leq 4$. If there is no autocorrelation, $\hat{\rho} = 0$ and $d = 2$. In the case of perfect positive autocarrelation, $\hat{\rho} = 1$ and $d = 0$ whilst $\hat{\rho} = -1$ and $d = 4$ for perfect negative autocarrelation. The statistic uses the upper, (d_U) and lower, d_L limits for the significance levels of d and the hypotheses to be tested are:

H_0 : No significant autocorrelation $Versus$ H_A : The is significant autocorrelation.

The test uses the following rules to accept or reject the null hypothesis of no autocorelation.

(1) Reject H_0 if $0 \leq d \leq d_L$ and $(4 - d_U) \leq d \leq 4$.

(2) Accept H_0 if $d_U \leq d \leq (4 - d_U)$.

(3) The result is inconclussive if $d_L \leq d \leq d_U$ and $(4 - d_U) \leq d \leq (4 - d_L)$

From Tables, the Durbin-Watson critical values for $k = 3$ variables at the 5 percent level of significance are $d_L = 1.61$ and $d_U = 1.74$. It follows from Table 6.15 that $d_U \leq d \leq (4 - d_U)$ and we conclude that there is no significant autocorrelation at the 5 percent level of significance.

Figure 6.9 shows the histogram plot of the residuals from the shorter data set which shows that they are approximately normally distributed. Thus, we conclude that the fitted ARDL

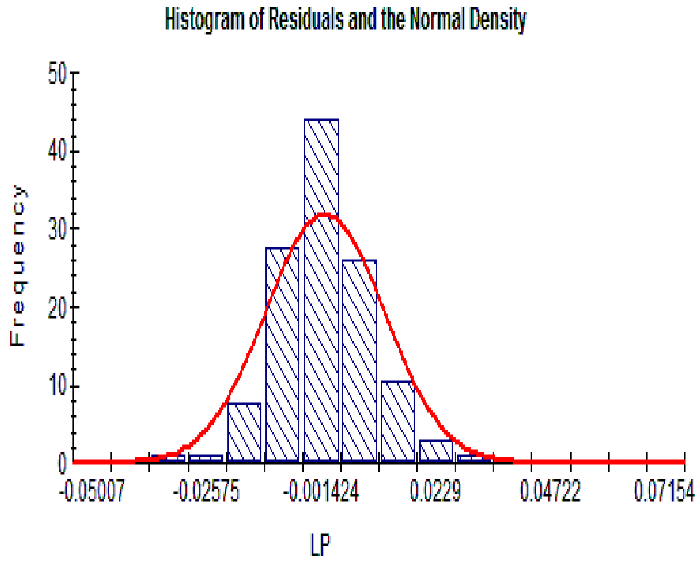


Figure 6.9: Histogram plot of the residuals.

model generally passes all diagnostic tests in the first stage.

Following Pesaran and Pesaran (1997), the stability of the regression coefficients over time is evaluated by stability test. We consider here the plot of the cumulative sum of the recursive residual (CUSUM), which are based on repeatedly fitting the regression model to a steadly growing data set. The idea is to start with some data, add data one case at a time, refit the regression and use it to predict the next case. The deviation between the next case's LP_t and the prediction is the recursive residual. Like ordinary residuals, they are independently and identically distributed but have no problem of shortcomings in one part of the data being carried over to the other residuals (Galpin and Hawkins, 1984). If the CUSUM remains within the 5 percent critical bound, then the long-run coefficients of the import price equation are stable. Figure 6.10 shows the plot of the cumulative sum of the recursive residuals for the shorter data set. Since the CUSUM remains within the 5 percent

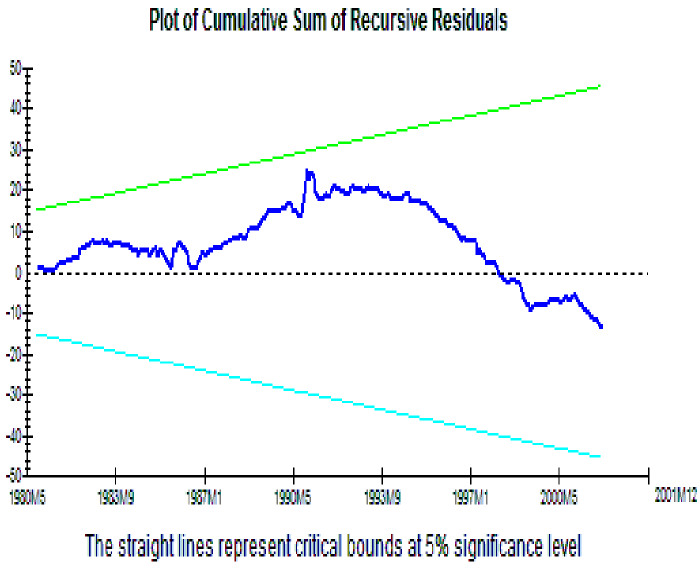


Figure 6.10: Plot of the cumulative sum of the recursive residual (CUSUM).

critical bound, we conclude that the long-run coefficients of the import price equation are stable, as suggested by the highly significant ECM coefficient in Table 6.17.

6.6 Comparison of the Models Using Simulated Data

We proceed to compare the PDL model and the Johansen type VECM by giving a summary of their pass-through estimates and the Akaike information criterion for the simulated data in Table 6.18.

	AIC	Pass-through Estimate
Simulated Series 1		
PDL	-5.886535	0.41581
VECM	-6.054265	0.770586
Simulated Series 2		
PDL	-5.678866	0.51935
VECM	-5.955511	0.702548
Simulated Series 3		
PDL	-5.830479	0.37147
VECM	-6.010591	0.778090
Simulated Series 4		
PDL	-5.968304	0.3495
VECM	-6.001560	0.778090
Simulated Series 5		
PDL	-5.866994	0.40224
VECM	-5.994532	0.785310
Simulated Series 6		
PDL	-5.765977	0.45306
VECM	-5.973797	0.785097
Simulated Series 7		
PDL	-5.740151	0.47829
VECM	-5.853158	0.764974
Simulated Series 8		
PDL	-5.847849	0.42992
VECM	-5.935488	0.772323
Simulated Series 9		
PDL	-5.932487	0.366657
VECM	-6.069086	0.760745
Simulated Series 10		
PDL	-5.827382	0.36487
VECM	-6.025376	0.783918

Table 6.18: Results on information criteria and exchange rate pass-through estimates.

We report the AIC values for the import price equation in the VECM only since we are interested in pass-through into import prices. We consider here 10 simulated data sets. Since the two methodologies perform almost equally well on the basis of AIC (although in all cases, the information criterion values under the PDL model are marginally less that those under the VECM), we consider alternative ways of comparing them. A natural alternative is to look at the variance of the parameter estimates (parameter stability) for each model and bias.

We calculate the variance and bias of the pass-through estimates, denoted here by $\hat{p}$ for each methodology using the respective formulae:

$$Var(\hat{p}) = \frac{\sum_{j=1}^{n}(\hat{p} - mean(\hat{p}))}{n-1} \tag{6.17}$$

and

$$Bias = \frac{\sum_{j=1}^{n}(p - \hat{p})}{n} \tag{6.18}$$

where $n = 10$, the number of simulated data sets. They are reported in Table 6.19. The

	PDL	VECM
Standard deviation	0.055542	0.02453974
Bias		
Statistical approach	0.5848833	0.2318319
Econometric approach	0.3469033	-0.0061481

Table 6.19: Results on standard deviation and bias of pass-through estimates from the two methodologies.

standard deviation of pass-though estimates from the PDL model, though in itself small, is more than twice that of the VECM for the simulated data set. This means that parameter values from the PDL model are less stable than those under the VECM using the same simulated data. Further, under the assumption of true pass-through using the statistical and econometric approaches, the bias of pass-through estimates from the PDL model is far too large compared to that under the VECM as seen from Table 6.19.

However, for the purpose of comparing the models, we report the mean squared error (MSE), defined as the expected value of the amount by which the estimator differs from the quantity to be estimated. It is a measure of how well the models explain a given set of observations and is given by

$$
\begin{aligned}
MSE(\hat{p}) &= E[(\hat{p}-p)^2] \\
&= E[(\hat{p}-E[\hat{p}]+E[\hat{p}]-p)]^2 \\
&= E[(\hat{p}-E[\hat{p}])]^2+[E(\hat{p})-p]^2+2E[(\hat{p}-E[\hat{p}])(E[\hat{p}]-p)] \\
&= Var(\hat{p})+(Bias[\hat{p}])^2
\end{aligned} \tag{6.19}
$$

The MSEs for the pass-through estimators from the two models is given in Table 6.20. We

	PDL	VECM
MSE		
Statistical approach	0.34517339	0.05434823
Econometric approach	0.12344742	0.000639997

Table 6.20: Mean squared errors of the pass-through estimators from the PDL and VEC models.

note that a mean squared error value of zero means the estimator predicts observations of the parameter with perfect accuracy. Hence, zero is the ideal value and forms the basis for the least squares method of regression analysis. However, although other MSE values are meaningless in and of themselves, they are useful for model comparison purposes, with the smallest MSE generally interpreted as best explaining the variability in the observations.

As can be seen from Table 6.20, the MSE values under the statistical approach to estimating exchange rate pass-through are higher than those under the econometric approach. This may be because distributed lag models are more statistical, and thus devoid of economic meaning whereas ECMs have economic interpretation. This conclusion is strengthened by the observation that the MSE under the econometric approach for the PDL model is higher than the one under the statistical approach for the Johansen type VECM. This may be attributed to the large bias values for pass-through estimates under the PDL models regardless of whether a statistical or economic approach is used. This is consistent with the reviewed literature which suggests that pass-through estimates from early studies which employed PDL models are potentially biased. As a result, we reach the conclusion that, on the basis of this simulation study, the Johansen type VECM is superior to the PDL model for estimating the pass-though relationship.

Having settled for the Johansen type VECM, we seek to establish the extent of the difference between MSE values under the statistical and econometric approaches for this methodology. From Table 6.20, the ratio of the MSE under the VECM for the statistical approach to that of the economic approach is over 1 : 84. In fact, to 2 decimal places, the MSE under the VECM for the econometric approach is zero, indicating that the pass-through estimate perfectly predicts observations of the true pass-through.

Further, a study of the literature shows that time series properties of the data are crucial, meaning that we may need to establish how each of the methodologies accounted for such properties. In fitting the PDL model, we used first differences of the data to avoid the risk of running spurious regressions since the series are nonstationary. But this also presents a problem in that using differenced data is like working with a nested version of the error correction model, which is potentially mis-specified. Besides, it is clear from equation 1.9 that pass-through is a levels relationship, meaning differencing to stationarity may lead to incorrect results. On the other hand, the Johansen type VECM works with data in levels and where the time series constitutes a system that moves together in time and has a long-run equilibrium relation. Above all, the sample from January 1980 to December 2001 includes the period where there has been major changes in South Africa, particularly a change in the government, an end to the sanctions and changes in economic policy. But as can be seen from the time series plot of the data in Figure 6.2, there is no evidence from the data to suggest that a structural break has occurred. Hence, we say that on the basis of this simulation study, the two methodologies perform equally well on the AIC but the VECM has stable parameters and is correctly specified than the PDL model.

6.7 Fitting the ARDL model and the Johansen-type VECM to the Longer Data set

Having concluded that the PDL model is potentially mis-specified, we fit the ARDL model and the Johansen-type VECM to the longer South African data set, the sample from January 1980 to April 2007 to estimate exchange rate pass-through. We only give a summary of results since the full implimentation of the methodologies have already been reported.

6.7.1 Pass-through Estimate Using the Johansen-type VECM

Unit root tests suggested that all the data series are $I(1)$ and a $VAR(3)$ model was selected after runing an Eviews program in Appendix A on the basis of AIC. Time series plots of the series are given in Figure 6.11. The selected $VAR(3)$ model passed diagnostic tests

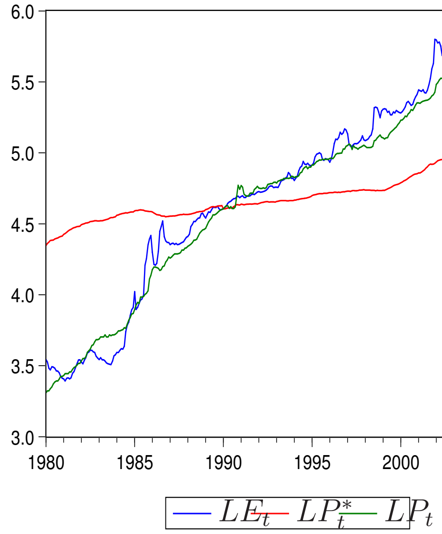


Figure 6.11: Time series plots of the longer South African data series, January 1980 to April 2007.

for stability, stationarity, residual autocorrelation, statistical independence of residuals and white noise behaviour of residuals. Both the unrestricted Trace and Maximum Eigenvalue co-integration rank tests selected a single co-integration relationship between the variables. The results for the co-integration equation and adjustment coefficients are summarised in Table 6.21. This shows that about 72% percent of exchange rate changes are passed-through to import prices when the Johansen-type VECM is fitted to the longer South African data set.

6.7.2 Pass-through Estimate Using the ARDL Co-integration Approach

The resulting ARDL model from applying the ARDL co-integration approach for the longer South African data set on the basis of Schwarz Bayesian criterion is given in Table 6.22.

Restricted Co-integrating Coefficients		
LP_t	LE_t	LP_t^*
1.000000	-0.727621	-0.727621
(0.00000)	(0.02024)	(0.02024)
Adjustment Coefficients		
$D(LP_t)$	-0.035678	
	(0.00871)	
$D(LE_t)$	0.026598	
	(0.02276)	
$D(LP_t^*)$	-0.002984	
	(0.00234)	

Table 6.21: The co-integration equation and adjustment coefficientsests for the single co-integrating vector.

Because of the high F-statistic, long-run coefficients and their respective asymptotic standard

Regressor	Coefficient	Standard Error	T-Ratio	Prob.
LP_{t-1}	0.93581	0.0087483	106.9706	0.0000
LE_t	0.052425	0.0074461	7.0406	0.0000
LP_t^*	0.023842	0.0081700	2.9183	0.004
Constant	-0.052356	0.028512	-1.8363	0.067
R-Squared	0.99963	R-Bar-Squared	0.99963	
S.E of Regression	0.012625	F(3,320)	290092.4	0.0000
Residual Sum of Squares	0.051003	Log-likelihood	958.8364	
AIC	954.8364	SBC	947.2749	
DW-statistic	1.7520			

Table 6.22: Parameter estimates for the ARDL(1,0,0) model selected based on the Schwarz Bayesian Criterion.

errors are determined in the first step and are reported in Table 6.23. This gives an estimate of about 81% of changes in exchange rates being passed-through to import prices using the longer South African data set.

Table 6.24 reports the short-run adjustment coefficients obtained from the error correction version of the fitted ARDL(1,0,0) model.

Regressor	Coefficient	Standard Error	T-Ratio	Prob.
LE_t	0.81672	0.030573	26.7135	0.0000
LP_t^*	0.37144	0.10675	3.4793	0.001
Constant	-0.81564	0.39717	-2.0536	0.041

Table 6.23: ARDL(1,0,0) model long-run coefficients selected by the Schwarz Bayesian Criterion.

Regressor	Coefficient	Standard Error	T-Ratio	Prob.
ΔLE_t	0.052425	0.0074461	7.0406	0.0000
ΔLP_t^*	0.023842	0.0081700	2.9183	0.004
$\Delta Constant$	-0.052356	0.028512	-1.8363	0.067
ECM_{t-1}	-0.064190	0.0087483	-7.3374	0.0000
R-Squared	0.16677	R-Bar-Squared	0.15896	
S.E of Regression	0.012625	F(3,320)	21.3491	0.0000
Residual Sum of Squares	0.05100340350	Log-likelihood	958.8364	
AIC	954.8364	SBC	947.2749	
DW-statistic	1.8265			

Table 6.24: Error correction representation for the selected ARDL(1,0,0) model based on the Schwarz Bayesian Criterion.

Thus, both methodologies gives pass-through estimates for the longer data set which are different from their respective estimates for the sample from January 1980 to December 2001 (52% for the PDL model and 77% for the Johansen type VECM). This is consistent with the findings in the literature where different exchange rate pass-through estimates have been reported in studies for the same country. According to the reviewed literature, pass-through estimates are sensitive to the methodology and the data used in the study. In this case, these differences could be due to the data set, since we used the same methodologies for both the shorter and longer data sets. One possible explanation could be the low speed of adjustment coefficients. Since the system takes long time lags to adjust back to the long-run equilibrium relation, the methodologies can only report roughly the same pass-through estimates provided the data coincides with periods when equilibrium was restored following a shock.

According to Pahlavani *et al* (2005), the ARDL cointegration approach has a number of advantages over the Johansen co-integration techniques. First, unlike the latter which requires large data samples for validity, the ARDL cointegration approach is more statistically significant in small samples.

Further, the ARDL co-integration approach does not require all of the regressors to be integrated of the same order. In fact, it is applicable even if the regressors are $I(1)$ or $I(0)$. Hence, since standard unit root tests are susceptible to misleading results particularly in the presence of structural breaks, the ARDL model yields consistent estimates of the coefficients irrespective of whether the underlying regressors are I(1) or I(0), thus providing robustness to the results, assuming variables are not $I(2)$ and above (Pesaran *et al*, 2001).

Another advantage of the ARDL co-integration approach over the Johansen co-integration techniques according to Pahlavani *et al* (2005) is that it avoids the burden of making several choices. These include the number of variables to be included in the VAR, treatment of deterministic elements, and the appropriate VAR lag order. The Johansen co-integration techniques, according to Pesaran and Smith (1998), is highly sensitive to these choices and decisions. Above all, it is possible with the ARDL approach for different variables to have different optimal number of lags, which is not permitted in Johansen-type models.

Thus, we conclude that if we are not sure about the integration order of the data, it is more appropriate to apply the ARDL cointegration approach for empirical work. However, if the variables are all integrated of the same order and the sample is large enough, the Johansen-type VECMs can be used.

Chapter 7

Overall Conclusions and Recommendations for Further Work

The econometric results reported in this research report on the basis of the simulation study, suggest that error correction models are superior to polynomial distributed lag models for estimating exchange rate pass-through. Reasons for the poor performance of the polynomial distributed lag model include potential mis-specification. Exchange rate pass-through is a levels relationship (equation 1.9), but working with data in levels when fitting polynomial distributed lag models results in spurious results becoming a major concern. The alternative of working with data in first differences (as is the case in this research report) also imply working with a nested version of the VECM with a "no cointegration" restriction and thus, potentially misspecified. Further, unlike error correction models, the PDL model is more statistical, without much econometric meaning. Hence, exchange rate pass-through results of this type of approach are not valid.

Thus, we conclude that newer methodologies which allow for co-integration should be used to estimate the exchange rate pass-through since it is a long-run relationship. The methodologies considered in this study include the Johansen type VECM (a multivariate cointegration technique) and the ARDL "single equation" cointegration approach. The former has a number of advantages over the latter namely (i) it is a simple procedure in that it allows the co-integration relationship to be estimated by OLS once the lag order of the model is identified, (ii) it does not require the pre-testing of the variables included in the model for unit roots provided none of them is $I(2)$ and above, (iii) the test is relatively more efficient in small sample sizes and (iv) it makes it possible to easily assess exchange rate pass-through, both in the short-run and in the long-run, the latter being defined as the static equilibrium solution. We, however, conclude that if we know the unit root properties of the data and provided they are integrated of the same order, then the Johansen type VECM will also yield consistent estimates of exchange rate pass-through. Otherwise, assuming $I(0)$ and /or $I(1)$ regressors, the ARDL cointegration procedure is generally the more appropriate model for empirical work.

We also conclude that exchange rate pass-through to South Africa's import prices is incomplete and that estimates are highly sensitive to the methodology and the data used in the study. Both the Johansen type and the ARDL cointegration approaches gave different pass-through estimates when each was applied to the shorter and longer South African data samples. Based on the coefficients of the ECM_{t-1} of -0.067964 and -0.064190 under the ARDL co-integration approach in Tables 6.17 and 6.24 respectively, we conclude that the deviation from long-run exchange rate pass-through to import prices in South Africa is corrected by about 7 percent in the current month. This finding shows that the speed of adjustment is really very low.

Having explored the pass-through relationship to South Africa's import prices this far, we give below some recommendations for further work. Firstly, we compared the methodologies using information criteria and mean squared error. The latter was computed via a simulation study and based on the assumption that the pass-through estimate from the model used to generate the data is the true pass-through. Research where alternative ways of calculating true pass-through are used will also be interesting. Secondly, we simulated data from the fitted VAR model after showing the link between VARs and ARDL models. An alternative is to simulate data from equation 3.16, which according to Hendry (1995) is the general case of every single-equation model in empirical time series. This however requires the series LE_t and LP_t^* to be specified. We recommend explaining these series possibly by general autoregressive conditional heteroscedasticity (GARCH) models which may capture volatility that is generally associated with these series. Thirdly, we recommend looking at pass-through at a more disaggregated level since the pass-through coefficient may be influenced by the extent of the homogeneity and substitutability of the concerned goods.

Appendix A

Vector Autoregression Lag Order Selection

```
..................................................................
' VAR lag order selection
..................................................................
'change path to program path
%path = @runpath
cd %path
' load workfile
load workfile name here
.....................................................................
' estimate VAR
.....................................................................
smpl Specify sample here (eg 1980:1 2001:12)
var var1.ls 1 k series1 series1 series3 @ c
....................................................................
' lag length criteria
...................................................................
!pi = @acos(-1)
!c = var1.@neqn*(1+log(2*!pi))
' unmodified LR test (exactly replicate Table 4.4, p.127)
' 1st column: (unmodified) LR statistic
' 2nd column: p-value
!m = @rows(mlag)-2
matrix(!m,2) tab44
!df = var1.@neqn * var1.@neqn    ' degrees of freedom of test
for !r=!m to 1 step -1
```

```
   tab44(!r,1) = 2*(mlag(!r+1,1) - mlag(!r,1))
   tab44(!r,2) = 1 - @cchisq(tab44(!r,1),!df)
next
```
....

Appendix B

The R code for Simulating the Series LP_t, LE_t and LP_t^*

```
library("MASS")
library("foreign")
library("mAr")
library("lattice")
library("coda")
library("KernSmooth")
library("xtable")
library("MSBVAR")
dataset=c()
data=read.csv("p_t2.csv")
fit=mAr.est(data,3,3)
a=rbind(fit$wHat[1],fit$wHat[2],fit$wHat[3])
h=matrix(c(1.487527e-04,1.773492e-05,3.459075e-08,1.773492e-05,9.345129e-04,-4.554930
p1=rbind(data[3,1],data[3,2],data[3,3])
p2=rbind(data[2,1],data[2,2],data[2,3])
p3=rbind(data[1,1],data[1,2],data[1,3])
for(i in 1:260)
{
b=fit$AHat[,1:3]%*%p1
f2=fit$AHat[,4:6]
c=f2%*%p2
f3=fit$AHat[,7:9]
d=f3%*%p3
tot=a+b+c+d+rgen
atot=t(tot)
```

```
dataset=rbind(dataset,atot)
randomn=rmultnorm(1,matrix(c(0,0,0),3,1),vmat=matrix(c( h[1,1], h[2,1], h[3,1],h[1,2]
rgen=rbind(randomn[1],randomn[2],randomn[3])
p3=p2
p2=p1
p1=tot
}
dataset
```

Appendix C

ACFs and PACFs of Differenced Logged Domestic Price

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.167	0.167	7.4352	0.006
		2	0.120	0.095	11.274	0.004
		3	0.084	0.052	13.150	0.004
		4	-0.097	-0.134	15.697	0.003
		5	-0.178	-0.167	24.267	0.000
		6	-0.071	-0.004	25.640	0.000
		7	-0.052	0.016	26.383	0.000
		8	0.079	0.121	28.077	0.000
		9	0.199	0.165	38.940	0.000
		10	0.049	-0.058	39.595	0.000
		11	0.112	0.034	43.087	0.000
		12	0.145	0.107	48.903	0.000
		13	0.062	0.088	49.972	0.000
		14	-0.025	-0.016	50.147	0.000
		15	-0.055	-0.072	50.995	0.000
		16	-0.071	-0.035	52.411	0.000
		17	0.014	0.074	52.467	0.000
		18	0.001	0.026	52.467	0.000
		19	-0.002	-0.017	52.468	0.000
		20	-0.012	-0.110	52.513	0.000
		21	0.111	0.063	56.068	0.000
		22	0.000	-0.009	56.068	0.000
		23	-0.042	-0.040	56.586	0.000
		24	0.010	-0.000	56.618	0.000
		25	0.068	0.074	57.975	0.000
		26	-0.056	-0.068	58.914	0.000
		27	0.036	0.054	59.289	0.000
		28	0.016	0.022	59.362	0.000
		29	-0.014	-0.014	59.421	0.001
		30	0.103	0.078	62.564	0.000
		31	-0.026	-0.037	62.774	0.001
		32	-0.007	0.019	62.787	0.001
		33	0.046	0.022	63.415	0.001
		34	0.001	-0.014	63.416	0.002
		35	-0.064	-0.031	64.667	0.002
		36	0.034	0.022	65.032	0.002

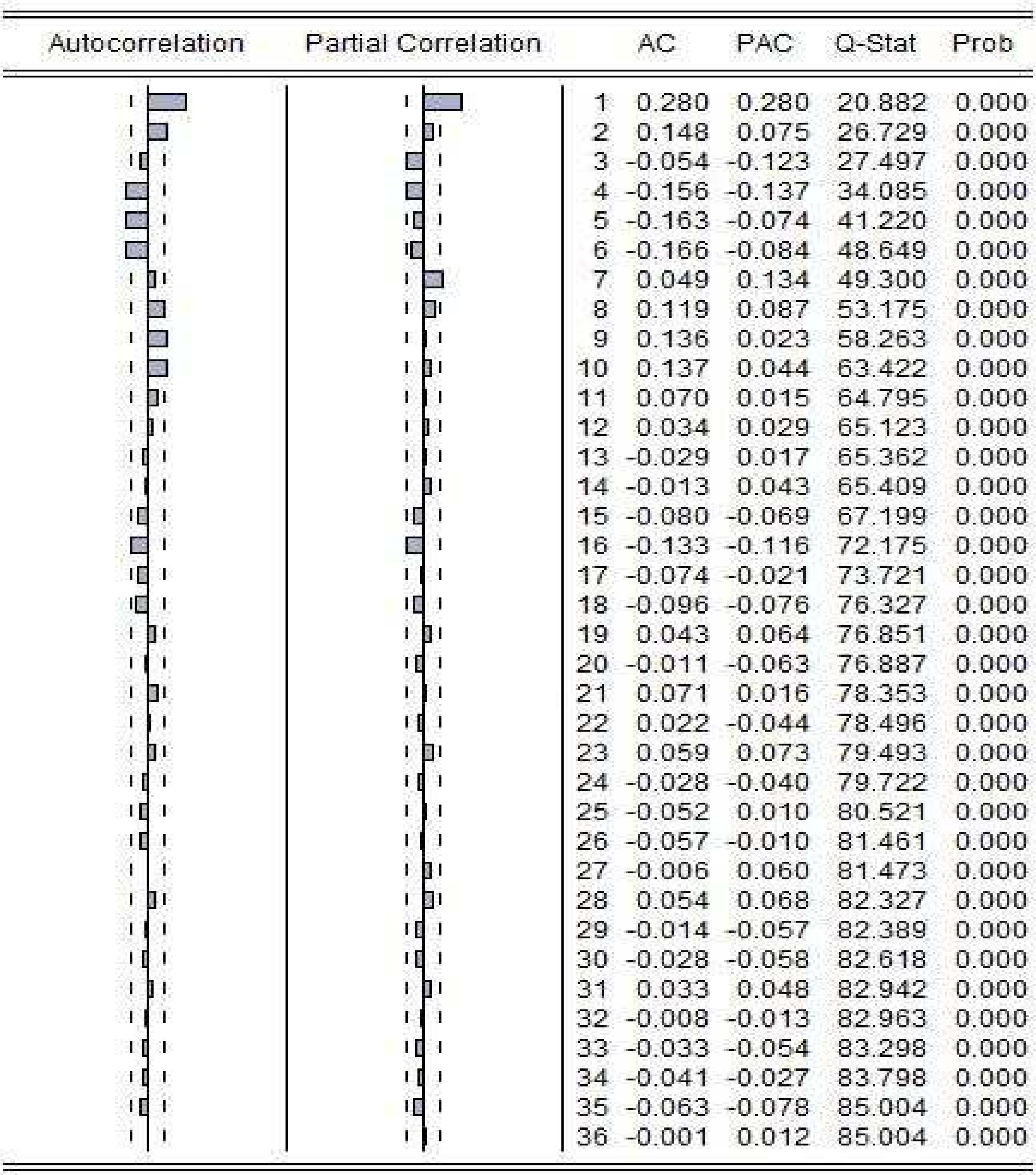
Appendix D

ACFs and PACFs of Differenced Logged Foreign Price

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.469	0.469	58.502	0.000
		2	0.380	0.205	96.962	0.000
		3	0.363	0.167	132.20	0.000
		4	0.309	0.074	157.91	0.000
		5	0.315	0.108	184.77	0.000
		6	0.295	0.066	208.42	0.000
		7	0.183	-0.081	217.49	0.000
		8	0.172	-0.005	225.61	0.000
		9	0.178	0.030	234.26	0.000
		10	0.233	0.123	249.27	0.000
		11	0.233	0.067	264.32	0.000
		12	0.171	-0.024	272.44	0.000
		13	0.179	0.033	281.38	0.000
		14	0.149	-0.025	287.57	0.000
		15	0.116	-0.048	291.37	0.000
		16	0.076	-0.081	293.02	0.000
		17	0.088	0.022	295.22	0.000
		18	0.047	-0.020	295.85	0.000
		19	0.035	-0.014	296.21	0.000
		20	0.057	0.031	297.15	0.000
		21	0.044	0.000	297.70	0.000
		22	-0.009	-0.068	297.72	0.000
		23	0.014	-0.010	297.78	0.000
		24	0.042	0.042	298.30	0.000
		25	-0.064	-0.128	299.50	0.000
		26	-0.033	0.005	299.82	0.000
		27	-0.038	0.002	300.25	0.000
		28	-0.022	0.050	300.39	0.000
		29	-0.042	-0.024	300.91	0.000
		30	-0.039	-0.003	301.35	0.000
		31	-0.042	0.010	301.88	0.000
		32	-0.064	-0.043	303.11	0.000
		33	-0.052	-0.003	303.94	0.000
		34	-0.064	-0.051	305.20	0.000
		35	-0.039	0.061	305.67	0.000
		36	-0.028	0.049	305.91	0.000

Appendix E

ACFs and PACFs of Differenced Logged Exchange Rate



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.280	0.280	20.882	0.000
		2	0.148	0.075	26.729	0.000
		3	-0.054	-0.123	27.497	0.000
		4	-0.156	-0.137	34.085	0.000
		5	-0.163	-0.074	41.220	0.000
		6	-0.166	-0.084	48.649	0.000
		7	0.049	0.134	49.300	0.000
		8	0.119	0.087	53.175	0.000
		9	0.136	0.023	58.263	0.000
		10	0.137	0.044	63.422	0.000
		11	0.070	0.015	64.795	0.000
		12	0.034	0.029	65.123	0.000
		13	-0.029	0.017	65.362	0.000
		14	-0.013	0.043	65.409	0.000
		15	-0.080	-0.069	67.199	0.000
		16	-0.133	-0.116	72.175	0.000
		17	-0.074	-0.021	73.721	0.000
		18	-0.096	-0.076	76.327	0.000
		19	0.043	0.064	76.851	0.000
		20	-0.011	-0.063	76.887	0.000
		21	0.071	0.016	78.353	0.000
		22	0.022	-0.044	78.496	0.000
		23	0.059	0.073	79.493	0.000
		24	-0.028	-0.040	79.722	0.000
		25	-0.052	0.010	80.521	0.000
		26	-0.057	-0.010	81.461	0.000
		27	-0.006	0.060	81.473	0.000
		28	0.054	0.068	82.327	0.000
		29	-0.014	-0.057	82.389	0.000
		30	-0.028	-0.058	82.618	0.000
		31	0.033	0.048	82.942	0.000
		32	-0.008	-0.013	82.963	0.000
		33	-0.033	-0.054	83.298	0.000
		34	-0.041	-0.027	83.798	0.000
		35	-0.063	-0.078	85.004	0.000
		36	-0.001	0.012	85.004	0.000

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