Effects of Australian Inward FDI: a Time Series Approach

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Declaration

Unless otherwise acknowledged in the text or acknowledgements, the work presented in this dissertation is my own original work.

The word count this dissertation is 14,983 words, respectively. This consists of a gross word count (23530 words) less tables, figures and references (6,949 words), footnotes (976 words), title, declaration and acknowledgements (178 words), abstract (128 words) and contents (316 words).

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Abstract

This thesis examines the effects of inward FDI on economic growth, fixed capital formation, imports and exports for the case of Australia – an area where limited empirical research has been undertaken. A time series approach is chosen to model the variables dynamically and endogenously using quarterly real data from September 1985 to June 2019. This involved the estimation of a restricted vector error correction model, impulse response and variance decomposition analysis, and Granger-causality testing using the asymptotically-reliable Toda-Yamamoto (1995) procedure. Results revealed bi-directional causality running between FDI and imports, and showed that FDI was import-substituting in Australia. More importantly, there was no evidence to support claims made by the Australian government, various industry groups and several economists that inward FDI leads to economic growth, capital accumulation and increased exports.

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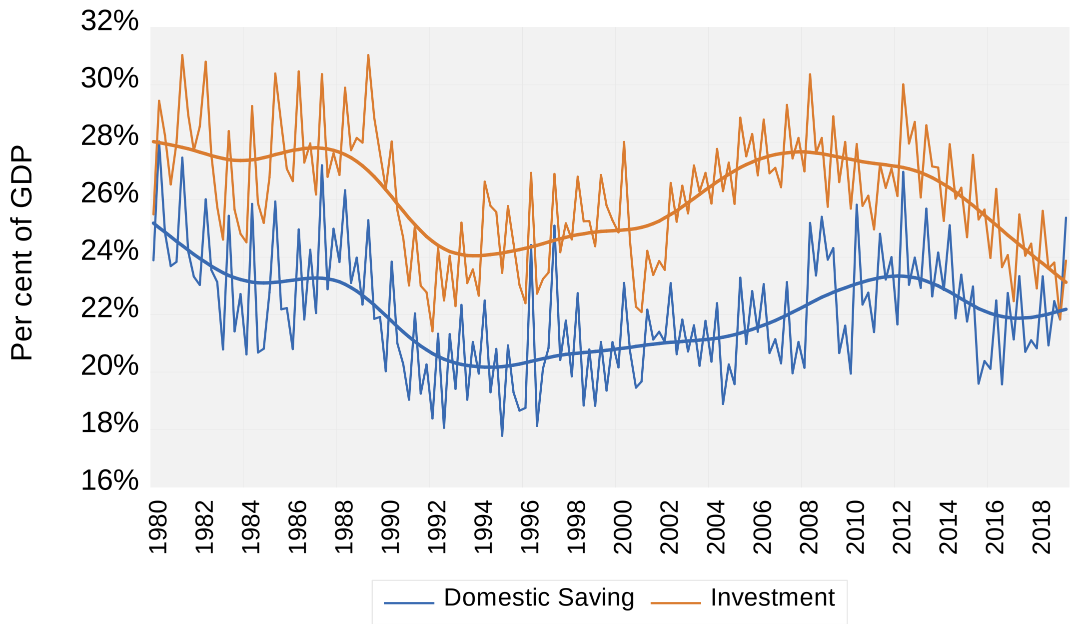
1 Introduction

Increased globalisation over the past three decades has been accompanied by a surge in foreign investment. The level of foreign investment in Australia has grown from $238 billion at the end of June 1989, to $3.69 trillion at the end of June 2019 – an average annual growth rate of nearly 10% (ABS 2019).

Foreign investment is widely thought to be critically important to the Australian economy, allowing Australians to enjoy higher standards of living than would otherwise be sustainable by financing the shortfall between domestic saving and investment. Depicted in the diagram below, this shortfall has averaged about 4% of GDP over the period from 1980-2019.

Figure 1a: Financing the gap between Australia's domestic saving and investment
Source: Australian Bureau of Statistics, Cat. 5206.0 – Australian National Accounts



The idea that foreign investment is beneficial makes intuitive sense – Australia is a resource-rich country with a small population and high capital demand, and has historically turned to overseas sources of financial capital to supplement domestic saving. This additional finance should add to both current consumption and fixed capital formation, and in turn support higher levels of economic growth.

The Australian Department of Foreign Affairs and Trade (DFAT) cites several additional mechanisms through which foreign investment is thought to benefit Australia. These include enhancing productivity growth through technology and knowledge augmentation, connecting Australian businesses to global value chains, encouraging competition, increasing trade opportunities and supporting local industry growth and job creation (DFAT 2019).

When an overseas entity establishes a new business, or acquires a 10% or higher stake in an Australian enterprise such that it is assumed to exercise some form of operational control, this is referred to as foreign direct investment (FDI). The other main form of foreign investment is known as portfolio investment, which refers to the purchase of equity or debt securities (e.g. stocks or bonds) representing less than 10% ownership – under such conditions the investor is assumed not to have any influence over business operations (IMF 2013).

Unlike portfolio investment, FDI usually involves a significant strategic commitment from the investor as it reflects some degree of operational involvement, and cannot be recalled quickly. Moreover, FDI is thought to be a vehicle not only for capital injection, but also for technology and skill transfers (spillovers) to the host economy. For this reason, FDI is of particular interest to economic policymakers.

In August 2018, Australia's then federal Minister for Trade Steven Ciobo noted that "*FDI underpins economic growth, improves productivity, enables the transfer of new technologies and drives exports*" (DFAT 2018). As a result, the Australian Government and its various agencies have invested considerable resources into attracting inward FDI.

Despite all of this, and the fact that Australia consistently ranks amongst the largest recipients of FDI in the world, there has been almost no research undertaken scrutinising the empirical consequences of FDI in the Australian context. Although the surge in FDI over the past three decades has led to the emergence of a significant body of literature on the subject, the Australian experience has been largely overlooked in terms of rigorous economic analysis.

This is the primary motivation for this thesis: to conduct a comprehensive empirical examination on the effects of Australian inward FDI on key macroeconomic variables including economic growth, fixed capital formation, imports and exports. The results will help determine the extent to which FDI is beneficial to the Australian economy, and have important policymaking implications – including whether the government should really be benchmarking its economic prowess on an ability to attract ever-increasing amounts of FDI.

A time series approach is chosen for two reasons. First, such an approach allows for an in-depth analysis of dynamic interrelationships between FDI and the other variables over time, and controls for heterogeneity and endogeneity in the data. Second, it circumvents the limitations of possibly erroneous and overly restrictive theoretical assumptions, giving the data a chance to "speak freely for themselves". The techniques used are drawn from a wide range of existing empirical FDI literature and modern applied time series econometrics.

The analysis contributes to the FDI literature in a number of ways. It is the only study besides Faeth (2006) to make use of time series data in analysing the effects of Australian inward FDI. Moreover, it is the first single-country study on the effects of Australian inward FDI to make use of both the Toda-Yamamoto procedure (to ensure Granger-causality tests are asymptotically valid) and a vector error correction approach (to conduct cointegration and impulse response analysis).

Results show that there FDI has a significant, bi-directional causal relationship with imports, and that FDI is import-substituting in Australia. However, there is no evidence to support the claim that FDI has a positive effect on economic growth, exports, or fixed capital formation. This has important policy implications related to the Australian Government's eagerness to attract inward FDI, and suggests that many of our preconceptions about the usefulness of inward FDI may be misplaced. This thesis is organised hereafter as follows. **Section 2** will give some necessary background on FDI in the Australian context. **Section 3** begins by examining the theoretical work on FDI, follows with a brief tour of the various frameworks employed in the global empirical literature, and concludes with a summary of empirical analyses as applied to Australia. **Section 4** describes the sources of data in detail, while **Section 5** outlines the method chosen in a step-by-step fashion and explains the underlying econometrics. The results are presented and their implications discussed in **Section 6**, and conclusions are drawn in **Section 7**.

2 FDI in the Australian Context

FDI can be measured in two different ways: stocks and flows. Stocks measure the aggregate level of direct investment in the economy at a given point in time. Flows measure the value of direct investment transactions over a given period. In absolute terms, Australia is one of the largest FDI recipient countries in the world, having the 13th-highest inward FDI stock globally, equivalent to 47.4% of GDP at the end of 2018 (UNCTAD 2019). Australia also recorded the world's 10th-highest average annual FDI inflow from 2014-2018, and the 8th-highest over 2009-2018. In relative terms, Australia's FDI performance is more ordinary. The graphs below compare Australia's ratio of inward FDI stock to GDP, and inward FDI flow to GFCF for the years 2009-2018, against the median OECD ratios and some reference countries.

Figure 1b: Ratio of inward FDI stock to GDP for Australia and selected countries, 2008-2018
Source: OECD Foreign Investment Statistics, Data, Analysis and Forecasts

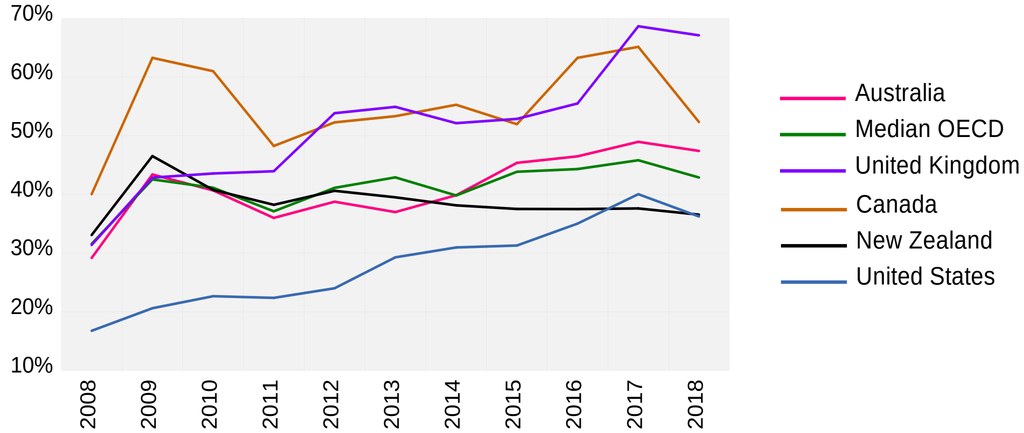


Figure 1c: Ratio of annual FDI flow to GFCF for Australia and selected countries, 2008-2018
Source: OECD Foreign Investment Statistics, Data, Analysis and Forecasts

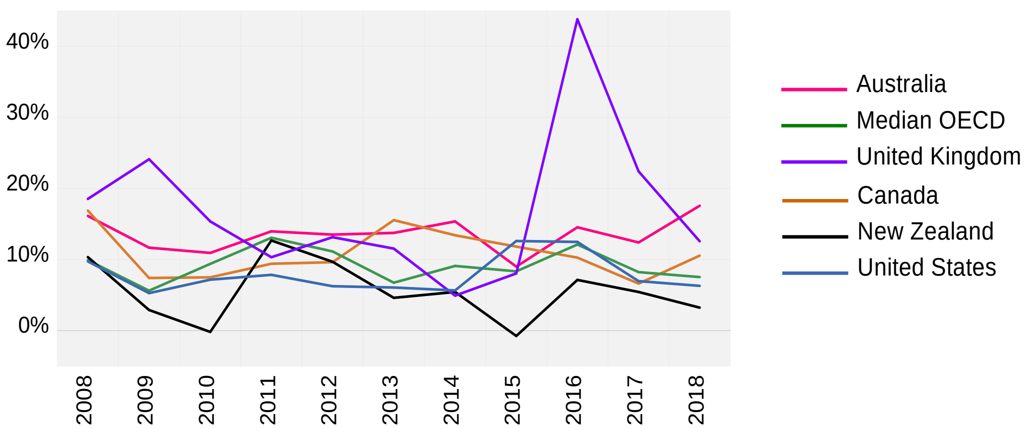
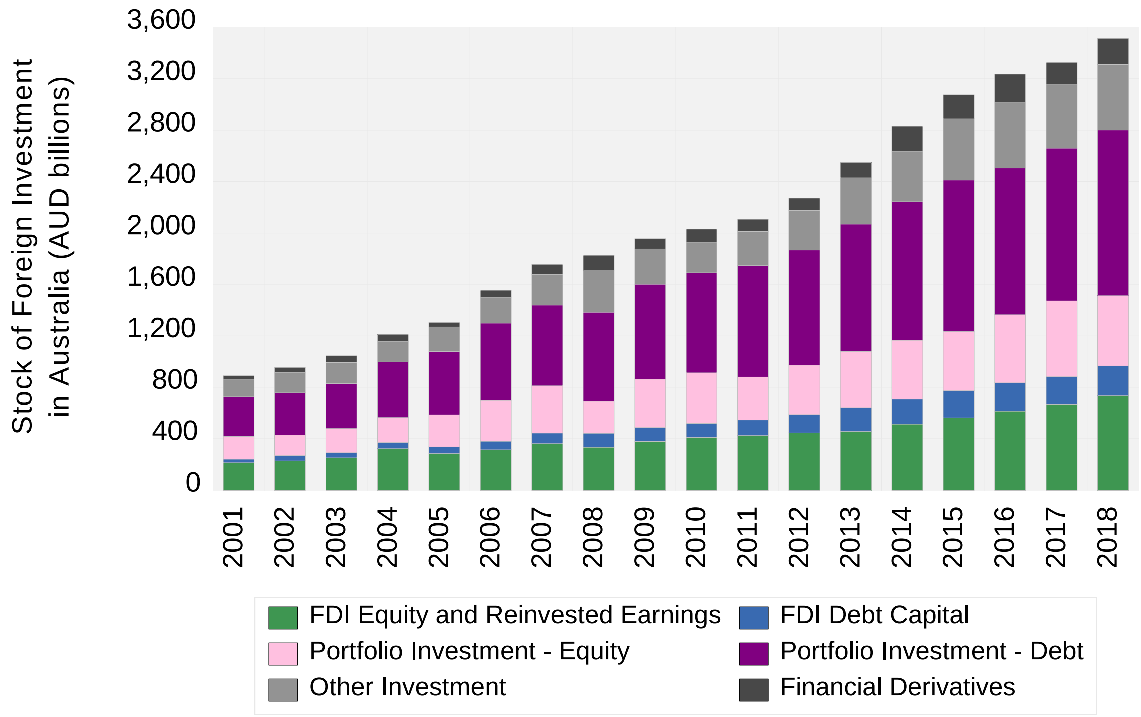


Figure 1b shows that Australia's inward FDI stock to GDP ratio is roughly in line with the median OECD level, and remains below the United Kingdom and Canada. **Figure 1c** shows that Australia's annual inward FDI flow as a proportion of total investment has been about 5% higher than the OECD median level on average over the last decade.

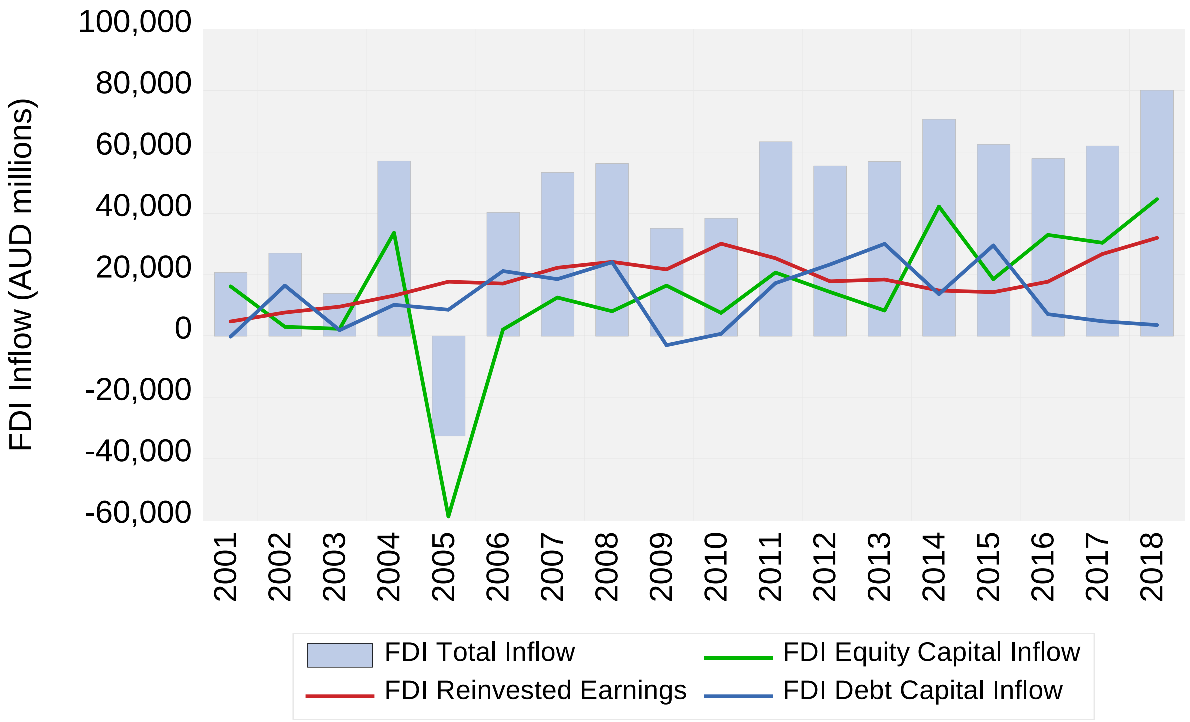
As at the end of 2018 the total stock of foreign investment in Australia was composed of FDI (28%), portfolio investment (52%), financial derivatives (6%) and other investment liabilities (14%). **Figure 1d** shows that FDI (the sum of FDI equity transactions, reinvested earnings and FDI debt capital) has comprised around one quarter of the total level of foreign investment in Australia since 2001.

Figure 1d: **Stock of total foreign investment in Australia by components, 2001-2018**
Source: Australian Bureau of Statistics, Cat. 5352.0 – International Investment Position



FDI inflows in any given year may be broken down by transaction type, as shown in **Figure 1e**. FDI equity capital is typically the most volatile as it reflects new transactions (greenfield projects and mergers and acquisitions) and deal flow may vary significantly from one year to the next[1]. On the other hand, reinvested earnings are relatively more stable. Note that it is possible to have negative FDI inflows since FDI is calculated according to the directional principle on a balance of payments basis (this is explained further in **Section 4**).

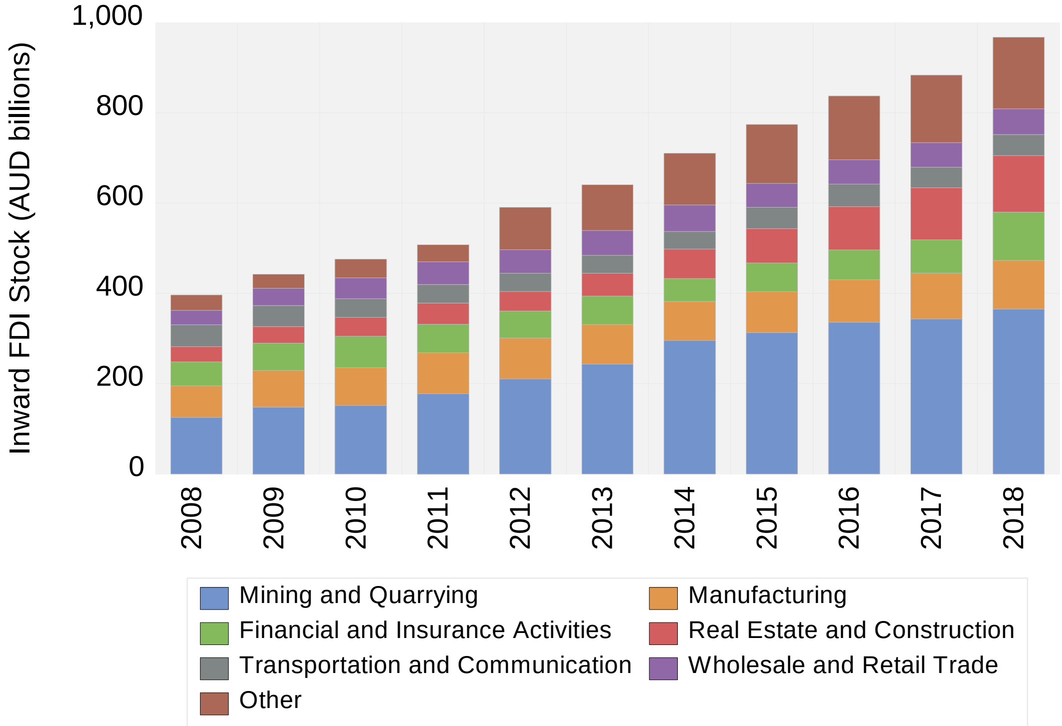
Figure 1e: **FDI annual inflow by components, 2001-2018**
Source: Australian Bureau of Statistics, Cat. 5352.0 – International Investment Position



[1] The large negative value for FDI equity capital inflow in 2005 is due to the relocation of News Corp headquarters from Australia back to the United States. This is explained further in Section 4.

It is also worth considering the distribution of Australia's inward FDI by industry. **Figure 1f** shows that most of the inward FDI stock is invested in mining (38%), followed by real estate and construction (13%), financial and insurance activities (11%) and manufacturing (11%). Other industries make up 14% of the FDI stock.[2] Notably, the share of mining-related FDI has increased from roughly 30% to nearly 40% over the 10-year period. The share of FDI in financial and insurance activities, as well as real estate and construction, has also increased.

Figure 1f: **FDI stock by broad industry classification, 2008-2018**
Source: Australian Bureau of Statistics, Cat. 5352.0 – International Investment Position



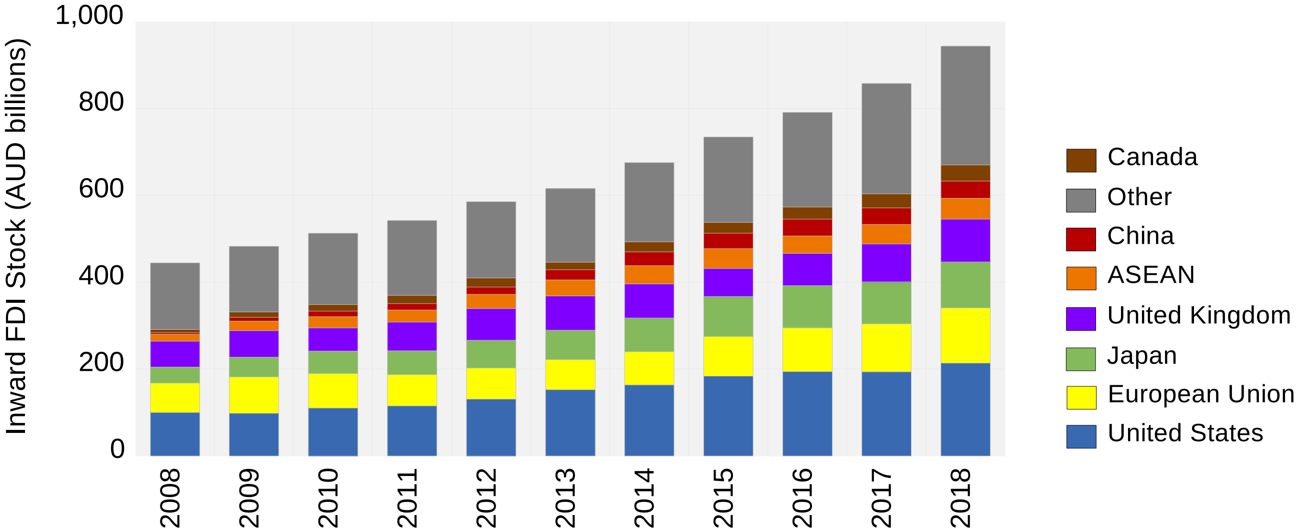
Australia's inward FDI may also be split by source country/region. Rankings according to stock and flow metrics are shown in **Table 1a**, while the share of Australia's inward FDI stock by source country/region is visualised over time in **Figure 1g**.

[2] Most of this investment is not allocated to any particular industry by the ABS.

Table 1a: Major sources of Australian inward FDI by country and region (stock and flow)					
Total FDI Stock		Average annual FDI Inflow, 2014-2018 (past 5 years)		Average annual FDI Inflow, 2009-2018 (past 10 years)	
Country/Region	Value (AUD billions)	Country/Region	Value (AUD millions)	Country/Region	Value (AUD millions)
United States	214,291	United States	14,087	United States	14,035
European Union	126,922	Japan	9,537	Japan	9,547
Japan	105,898	European Union	9,011	European Union	6,226
United Kingdom	98,747	United Kingdom	5,111	United Kingdom	5,682
ASEAN	47,722	China	3,840	China	3,955
China	40,105	Canada	3,247	ASEAN	3,191

Note: the European Union includes all of its current member states except the United Kingdom. China refers to the People's Republic of China and excludes Special Administrative Regions (SARs) and Taiwan. The Association of Southeast Asian Nations (ASEAN) refers to its 10 member nations. United States and United Kingdom are not inclusive of their overseas territories. *Source: ABS Catalogue 5352.0 – International Investment Position*

Figure 1g: FDI stock by source country/region, 2009-2018
Source: Australian Bureau of Statistics, Cat. 5352.0 – International Investment Position



The top investing nation in terms of both overall stock and average annual inflow, is the United States. However, the European Union, United Kingdom and Japan are also major FDI source countries, followed by ASEAN, China and Canada. Australia's inward FDI is drawn from a diverse set of countries and regions, with no country owning more than 23% of the total FDI stock.

Having examined the nature and composition of Australian inward FDI, it is now necessary to consider the global FDI literature from both a theoretical and empirical perspective, in order to inform the analysis that follows.

3 Literature Review

3.1 Theoretical studies on the effects of inward FDI

Despite the large amount of theoretical literature which attempts to explain the effects of FDI on growth, domestic investment and trade, the subject remains controversial. Neoclassical growth models assume exogeneous technological progress and labour force growth as the main drivers of long-run growth (Solow 1956, Cass 1965). These models, based on diminishing marginal returns to capital, suggest that FDI has only a short-run effect on growth by financing additional capital formation – equivalently to domestic investment.

The recent development of endogenous growth models, however, has given rise to arguments suggesting that FDI can serve as an important driver of growth in the long-run (Grossman and Helpman 1993, Barro and Sala-i-Martin 1997). Such models generally assume that FDI is more productive than domestic investment for two reasons. First, through capital accumulation, FDI is expected to promote economic growth and enhance productivity by encouraging incorporation of new inputs (including intermediate goods) and foreign technologies into the production function of the host economy (Blomstrom et al. 1992, Dunning 1993). Second, FDI may improve skill-levels and know-how in the host economy through technological spillovers, knowledge transfers, labour training, and/or new organisational practices. As the level of accumulated knowledge increases, the cost of innovation falls, leading to accelerated technological progress (Findlay 1978). In the presence of FDI, old goods can be produced with new and superior transferred technologies, leading to increasing returns via process innovation (De Mello 1997).

FDI may also embody new ideas, technologies and entrepreneurial skills, which are diffused in the host economy through training and exposure (Aharoni 1966, Kindleberger 1969). This is what differentiates FDI from other forms of foreign investment including portfolio investment and aid – FDI is thought to promote technological upgrading in the cases of start-up, marketing, and licensing arrangements, as well as leasing, management contracts and joint ventures (De

Mello and Sinclair 1995). Lall (1980) identified specific channels through which FDI spillovers could stimulate growth, which are summarised in by Lim (2001) and extended by Crespo and Fontoura (2007) – these are demonstration/imitation, labour mobility, exportation, competition and local linkages. In short, spillovers from foreign firms with superior technological endowments are likely to increase the host country's marginal productivity of capital, and thus promote long-run growth (Wang and Blomström 1992).

However, positive effects of FDI on long-run growth may persist only when certain conducive conditions in the host economy are met, without which FDI may be counterproductive. In this sense the impact of FDI depends greatly on the institutional context and policy environment of the host. Borensztein et al. (1998) argue that FDI has a positive effect on growth only when the host country has a sufficiently high level of human capital to allow it to exploit FDI spillovers. Campos and Kinoshita (2002) find that FDI has a positive impact on growth only in the case of pure technology transfer. Alfaro et al. (2004) and Durham (2004) find that local financial market development is a critical factor for FDI to contribute significantly to host-country economic growth, while Abramovitz (1986) argues that human capital, political stability and market openness are the necessary preconditions. Bhagwati (1978) hypothesises that FDI will be more efficient at promoting growth if the host adopts an export-promoting (trade-neutral) strategy, compared to an import-substituting (trade-distorting) one, by creating an economic climate more conducive to specialisation, economies of scale and technological upgrading.

Vernon's Product Cycle Hypothesis (Vernon 1966) showed that the maturation and standardisation of goods would eventually cause multinational enterprises (MNEs) to shift their production to developing "host" economies in an attempt to reduce costs, thereby increasing economic growth for the host. In contrast, Lall (2000) notes that MNEs are likely to exploit host economies when their main advantage is cheap unskilled labour, severely limiting the scope for growth-enhancing technological spillovers. Other theories predict that, in presence of existing trade, price, financial, and other distortions, FDI will adversely affect resource allocation and slow growth (Brecher and Diaz Alejandro 1977, Brecher 1983, Boyd and Smith 1992).

De Mello (1999) points out that the effect of FDI on long-run economic growth depends on the degree of substitution between FDI and domestic investment. A Schumpeterian view may conclude that FDI substitutes domestic investment through creative destruction, but this may be overly simplistic – Young (1993) emphasised that innovations embodied in FDI may in fact increase rents accruing to old technologies rather than reduce them. Noorzoy (1979) argued that FDI complements domestic investment when it flows to high-risk areas, or new industries where domestic investment is lacking.

Hymer (1976) argued that overall, FDI increases domestic investment through local borrowing, acceleration effects and lower prices, particularly when MNEs are vertically integrated. Ozawa and Castello (2003) hypothesised that FDI could accelerate domestic investment if host governments cooperate with MNEs to efficiently match location and ownership advantages. The two-sector model of Markusen and Venables (1999) predicts that FDI may crowd-out local investors and deter planned investment projects due to increased competition, especially when foreign rivals are technologically sophisticated.

Other scholars such as Huang (2003) and Braunstein and Epstein (2002) note that FDI has potentially crowding-out effect on domestic investment and adverse effects on growth. If MNEs are able to exploit advanced technologies, superior management techniques and other advantages to gain monopoly power over domestic firms, this suggests that FDI may substitute domestic investment in the long-run (Caves 1971, Hymer 1976). Monopoly power over indigenous firms may be increased further by market internalisation and location-specific advantages of MNEs (Dunning 1993).

New technologies brought with FDI may also accelerate obsolescence of traditional technologies in the host country, decreasing domestic investment. De Mello (1997) points out that in developing countries, complementarity between existing and FDI-related technology dominates, so that FDI is primarily a means to stimulate factor accumulation. In contrast, substitution dominates in developed countries, so that faster obsolescence of old technology drives increased productivity, increased absorption of new FDI-related innovations, and growth.

The FDI-trade nexus has also been analysed extensively in the theoretical literature, with FDI generally seen as an alternative to trade, resulting in local production (Krugman 1990). Dunning's (1993) OLI framework predicted that FDI would change the composition of trade, and its effects would depend on whether the FDI was intended to increase efficiency or to acquire strategic assets. Markusen's (1984) general equilibrium model showed that MNE activity led to trade creation, but its final effect would depend on whether intermediate input imports increased by more or less than final good imports decreased, and the market or export-orientation of FDI.

Building on this, Markusen's (2002) knowledge-capital model suggested that trade and FDI could be substitutes or complements depending on whether MNE activity was related to local sale or export. In turn, this depended on whether FDI was vertical or horizontal in nature, with the latter more likely to be trade-substituting.[3] Hanson et al. (2001) argued that the effect on host country trade depended on whether the FDI was production-oriented or distribution-oriented, with the latter more likely to increase imports more than exports.

3.2 Empirical studies on the effects of inward FDI

Though the theoretical literature provides powerful tools to understand the dynamics of inward FDI, its specific effects often boil down to idiosyncratic characteristics of the host economy and the nature of the FDI itself. A significant amount of empirical literature has emerged to deal with this problem, which can generally be divided into three groups by their methodology.

The first approach estimates models using cross-section data from developed and/or developing countries over a fixed time period or as an average of multiple separate time periods. The second approach uses panel and panel cointegration techniques to allow for country-specific and time-fixed effects, and/or country-specific cointegrating relationships. The third approach utilises time series methods such as vector autoregressive (VAR), vector error correction (VECM) or autoregressive

[3] Horizontal FDI refers to replicating similar activities across countries. Vertical FDI refers to locating different stages of production across countries.

distributed lag (ARDL) models combined with Granger-causality testing amongst variables, on single-country and multi-country cases. The following sub-section considers each type of approach and assesses its benefits and weaknesses.

3.2.1 Cross-section analyses

Turning our attention to the first group of cross-sectional analyses – the impact of FDI on growth is typically estimated using the following (or similar) equation:

$$g_{y,h} = \varphi_h + c_0 g_{k,h} + c_1 g_{f,h} + c_2 g_{\omega,h} + \varepsilon_h \tag{3.1}$$

In the equation above, g_i represents the growth rate of $i = y, k, f, \omega$ (respectively: output, domestic capital, an index of foreign-owned capital, and a vector of ancillary variables). Individual countries in the dataset are identified by the subscript h, while φ_h is added to allow for time-invariant individual country-effects, and ε is a white-noise disturbance term.

Blomstrom et al. (1992) uses this technique to conduct OLS estimations for 101 countries over the period 1960 to 1985, finding that FDI contributes positively to economic growth in higher-income countries but not in lower-income ones. Balasubramanyam et al. (1996) uses a similar approach and finds that growth-enhancing effects of FDI are stronger in countries with an export-promoting trade policy than those with an import-substituting one.

Borensztein et al. (1998) construct a cross-country endogenous growth model using seemingly unrelated regressions with instrumental variables, on data from 69 developing countries over two separate time periods, 1970-79 and 1980-89. They find that FDI contributes to economic growth through human capital augmentation and technology transfer, but that this positive impact is conditioned by the host economy’s stock of human capital which must be above a certain threshold for the effect to be significant. They also find that FDI more than proportionally increases total investment in the economy, i.e. that it is more efficient than domestic investment. Alfaro et al. (2004) uses cross-country data from 71 developing and developed economies and finds that FDI is growth-promoting conditional on local financial markets being sufficiently developed.

However, these cross-country analyses may still suffer from heterogeneity issues, given that production technologies, institutions and policies differ significantly across countries (Herzer et al. 2008). Critically, these studies do not consider bi-directional causality between FDI and growth and as such may suffer from severe endogeneity problems. Taking averages over multiple time periods also causes loss of dynamic information and degrees of freedom, which increases the risk of omitted variable bias. Choice of instrumentation within these models also represents a drawback, as suitable instruments are not always available (Nair-Reichert and Weinhold 2001).

3.2.2 Panel Analyses

Panel techniques using multi-year data improve upon pure cross-country estimations by correcting for country-specific differences in technology, production and other factors, which evolve through time, allowing for differentiated production functions (Islam 1995, De Mello 1997). A typical model is shown below, with the subscripts h and t denoting country and time period, respectively.

$$g_{y,ht} = \varphi_h + c_0 g_{k,ht} + c_1 g_{f,ht} + c_2 g_{\omega,ht} + \varepsilon_{ht} \qquad \textbf{(3.2)}$$

This specification is further improved by adding lagged terms of explanatory variables which help control for endogeneity bias. Dynamic panel specifications such as the system Generalised Method of Moments (GMM) panel estimator developed by Arellano and Bover (1995) and Blundell and Bond (1998) have become popular as they are able to handle endogenous independent regressors as well as control heteroskedasticity and autocorrelation problems across and within countries (Roodman 2009). They also allow for the explicit testing of Granger-causality.

Carkovic and Levine (2002) use this technique for 72 countries over the period 1960-1995 and do not find a robust positive relationship between FDI and economic growth, unlike the majority of previous work. Bengoa and Sanchez-Robles (2003) use it to analyse a panel of 18 Latin American countries from 1970-1999 and find FDI to be positively correlated with economic growth in host countries with adequate levels of human capital, economic stability and liberalised capital flows. However, traditional panel estimators suffer from the imposition of unrealistic homogeneous coefficients of on lagged explanatory variables, which may induce biases of the type identified by Pesaran and Smith (1992) if long-run dynamics are heterogeneous.

Nair-Reichert and Weinhold (2001) try to circumvent this problem using a mixed fixed and random technique, which allows for heterogeneous coefficients on the lagged dependent variables. Using data from 24 developing countries from 1971-1995, they find a causal relationship from FDI to growth on average, though the relationship between FDI, domestic investment and economic growth is highly heterogeneous across countries. De Mello (1999) addresses the heterogeneity issue using a mean group procedure for 32 OECD and non-OECD countries from 1970-1990. He finds that although FDI is generally growth-enhancing in the long-run, the relationship between FDI and domestic investment is negative for developed economies (i.e. substitution dominates) and positive for developing ones (i.e. complementary effects dominate).

3.2.3 Panel cointegration analyses

Standard panel analyses have been criticised for assuming a long-run or cointegrating relationship between levels of the variables *a priori*, which may cause specification issues (Irandoust and Ericsson 2001, Herzer et al. 2008). In response, modern studies have emphasised the use of panel cointegration techniques such as the one proposed by Pedroni (1995, 1999) to allow for individual country and time-fixed effects, as well as cointegrating vectors of different magnitudes between countries. Using this approach, Basu et al. (2003) examines a panel of 23 developing countries using data from 1978-1996 and finds bi-directional causality between FDI and growth for relatively open economies, and uni-directional causality from growth to FDI for relatively closed economies.

Li and Liu (2005) analyse a panel of 84 countries over the period 1970-1999 and find that FDI affects growth both directly and through interaction with human capital, but only when the technology gap between home and host economies is small. Choe (2003) uses Granger-causality testing on a panel of 80 developed and developing countries from 1971-1995, and finds uni-directional causality running from FDI to growth. Jain et al. (2014) uses panel cointegration methods to examine the FDI-domestic investment nexus in 22 emerging economies, finding bi-directional causality in Asia over the period 1995-2007.

The above approach suffers from a number of issues. A few cointegrating relationships may lead to rejection of the null hypothesis of no cointegration across the panel (Gutierrez 2003). Strauss and Wohar (2004) note that in the case of only a few cointegrating relationships, panel cointegration techniques should not be applied uniformly across the panel and may lead to severe biases and erroneous determination of causality. Even more seriously, Banerjee et al. (2004, 2005) finds that cointegrating between-country relationships in a panel may lead to a false rejection of the null, that is, erroneous conclusion of within-country cointegrating relationships across the panel even if none exist.

3.2.4 Time series analyses

Given the econometric issues associated with panel models, several more recent studies have focused on the FDI-growth relationship using time series techniques for single countries or a handful of countries. These techniques allow for an intuitive presentation of variable dynamics and visualisation of responses to shocks, through impulse response functions and variance decomposition analysis. They also allow for feedback dynamics in multivariate systems.

Time series models typically require less *a priori* information about the variables under consideration than traditional OLS estimation, which may be advantageous if economic theory regarding interaction of those variables is inconclusive (Gujarati 2009). Moreover, single-country studies allow for a stronger and more focused analysis of the country-specific context underlying the variables being tested.

Shan (2002) estimates an unrestricted VAR model on quarterly data over the period 1986-1998 to determine the strength of causality between growth, FDI and a number of other variables in China. He finds two-way-causality between FDI and output growth, though the effect of FDI on output growth was weaker than that of output growth on FDI. Kim and Seo (2003) use the same technique to explore the relationship between FDI, domestic investment and growth in South Korea over the period 1985-1999. They find positive and significant effects for FDI on growth and vice versa, but also that domestic investment has a significantly negative effect on FDI.

Although the VAR technique controls for endogeneity and allows for dynamic feedback in multivariate systems, it is not without its drawbacks. VAR estimation requires all variables to be integrated of the same order, and can be sensitive to the choice of appropriate lag lengths. The size of the VAR model also requires higher data frequency to generate enough degrees of freedom for estimation, which is not always available.

If variables in a VAR model are found to be non-stationary and cointegrated, a vector error correction model (VECM) should be estimated instead (Lutkepohl and Kratzig 2004). This involves identification of the unique cointegrating vectors reflecting structural relationships between variables in the long-run, typically using the method popularised by Johansen and Juselius (1990).

Chakraborty and Basu (2002) use a cointegration and VECM framework to analyse the two-way link between FDI inflows and growth for India from 1974-1996, finding uni-directional causality running from GDP to FDI. Tang et al. (2008) use a VECM approach on Chinese data from 1978-2003 and show that the causal link between GDP and domestic investment is bi-directional, but there is only uni-directional causality from FDI to domestic investment, and FDI to GDP.

Some studies also conduct repeated analysis for multiple countries, estimating separate VARs and/or VECMs for each country under investigation. Srinivasan et al. (2011) use a VECM to examine the causal nexus between FDI and economic growth in SAARC[4] countries for the years 1970-2007, finding bi-directional causality between GDP and FDI for the selected SAARC nations except India. Liu et al. (2009) perform multivariate causality tests within a VECM framework revealing two-way causal connections between trade, inward FDI, and growth for most of the economies sampled.

If there are mixed orders of integration in a system, it is possible to estimate an autoregressive distributed lag (ARDL[5]) model and test for cointegration using the bounds test developed by Pesaran et al. (2001). If there is cointegration, it is then possible to estimate an error-corrected ARDL model to extract both short-run and long-run dynamics. Chakraborty and Mukherjee (2012) estimated an ARDL to examine quarterly Indian FDI, GDP and GFCF series from 1996-2009, finding uni-directional causality running from growth to FDI, and FDI to domestic investment. The ARDL approach only identifies the presence of cointegration, however, and not the cointegration rank, which is problematic if there are two or more unique cointegrating vectors in the system.

Time series studies focused on detecting Granger-causality have adopted the Toda-Yamamoto (1995) method, which is robust to varying orders of integration amongst the variables under investigation. Chowdhury and Mavrotas (2006) apply this technique to investigate the FDI-growth nexus in Chile, Malaysia and Thailand over the period 1969-2000. They find uni-directional causality from GDP to FDI for Chile and bi-directional causality for Malaysia and Thailand. Guru-Gharana and Adhikari (2011) use a similar method and find evidence of FDI-led growth in China. The Toda-Yamamoto procedure cannot, however, be used to perform impulse response or variance decomposition analysis (as with VAR and VECM methods) and yields information regarding only the direction of causality between variables, and not the magnitude.

[4] The South Asian Association for Regional Cooperation (SAARC) includes member states Afghanistan, Bangladesh, Bhutan, India, the Maldives, Nepal, Pakistan and Sri Lanka.
[5] ARDL models are infinite distributed lag models which contain lags of both the dependent variable and independent variable(s). For more detail see Pesaran and Shin (1995).

3.3 Main findings in the global empirical literature

3.3.1 The FDI-growth nexus

Most of the empirical evidence suggests a significant, positive relationship between FDI and growth in both developing and developed countries, with relatively few studies finding the effects to be insignificant and even fewer finding a negative relationship. However, this link is often highly sensitive to economic conditions in the host economy. Important influencing factors for the host (without which the FDI-growth relationship may be insignificant) are the level of human capital (Borensztein et al. 1998, Bengoa and Sanchez-Robles 2003, Li and Liu 2005), the level of financial market development (Bengoa and Sanchez-Robles 2003, Alfaro et al. 2004, Durham 2004) and the level of trade openness (Balasubramanyam et al. 1996, Zhang 2001, Chakraborty and Basu 2002). Time series analyses mostly find causality running from FDI to GDP, and bi-directional causality in many cases (Shan 2002, Chowdhury and Mavrotas 2006, Al Iriani 2007). The strength of the causal relationship (if any) is highly heterogeneous across countries.

3.3.2 The FDI-domestic investment nexus

There does not seem to be a consensus on whether FDI has a crowding-in or crowding-out effect on domestic investment (or any effect at all). Although many studies do find evidence of crowding-in (Bosworth et al. 1999, De Mello 1999, Tang et al. 2008, Al-Sadig 2013), an equally large number of studies find evidence of crowding-out (Agosin and Machado 2005, Wang 2010, Morrissey and Udomkerdmongkol 2012, Pilbeam and Oboleviciute 2012) and some find no effect (Lipsey 2000, Kim and Seo 2003, Farla et al. 2016).

The FDI-domestic investment relationship is found to be heterogeneous across countries and regions – for example, in a panel of 36 developing countries over the period 1970-1996, Agosin and Mayer (2000) find evidence of crowding-in in Asia, crowding-out in Latin America and no effect in Africa. Some more recent evidence points to a more nuanced relationship whereby FDI has short-term crowding out effects on domestic investment (related to creative destruction) but long-term crowding-in effects (as linkages are deepened) (Mody and Murshid 2005, Jude 2019). However, the matter remains controversial.

3.3.3 The FDI-trade nexus

While there are theoretical arguments that support both substitution and complementary relationships between FDI and trade (for both exports and imports) – empirical work generally finds that FDI has a uni-directional positive effect on exports (Hsiao and Hsiao 2006, Mahmoodi and Mahmoodi 2016, Sunde 2017, Cañal-Fernández and Fernández 2018). This occurs for a variety of reasons, including FDI increasing exports directly (Liu et al. 2001, Bouras and Raggad 2015), or because foreign affiliates are more export-oriented than local firms[6] (Barry and Bradley 1997). Indeed, some studies find FDI induces local firms are induced to become more export-oriented (Greenaway et al. 2004). The relationship was found to be positive and bi-directional in some cases (Pacheco-Lopez 2005, Goh et al. 2017), though other studies have found a negative relationship (Faeth 2006).

The relationship between FDI and imports is less well-studied, though most empirical literature suggests that FDI has a uni-directional positive impact on imports (Graham and Krugman 1995, Alguacil and Orts 2003, Wong and Tang 2009). An OECD (1999) study noted that FDI typically increased imports in host countries, and increased exports in the longer-term, though the extent of complementarity varied widely amongst countries.

[6] This is the case for Australia – see analysis by the ABS (2018).

3.4 Empirical Analyses of FDI in Australia

Despite Australia ranking consistently as one of the highest net importers of FDI globally, empirical research on the consequences of Australian inward FDI on key macroeconomic variables remains very limited.

An ABS (1998) business survey found that majority foreign-owned firms tended to export more than domestic firms. A later report also by the ABS (2004) found that the value of goods and services imports by majority foreign-owned firms far exceeded the corresponding value of exports, deteriorating the balance of payments position. In another survey of 270 foreign-owned businesses in Australia, Nicholas et al. (2003) found that overall, foreign affiliates were mainly focused on domestic production and local distribution of home-country goods and services.

A more recent ABS (2018) study commissioned by DFAT and Austrade, found that foreign-owned businesses had a higher export-to-sales ratio (12.4%) on average compared to Australian-owned businesses (9.5%) over the 2014-2015 period, though significant variation between countries was observed. The same study showed that although foreign-owned affiliates made up only 18.0% of all businesses in Australia, they contributed 20.8% of industry value added (AUD 222 billion) and 29.3% of exports (AUD 95 billion).

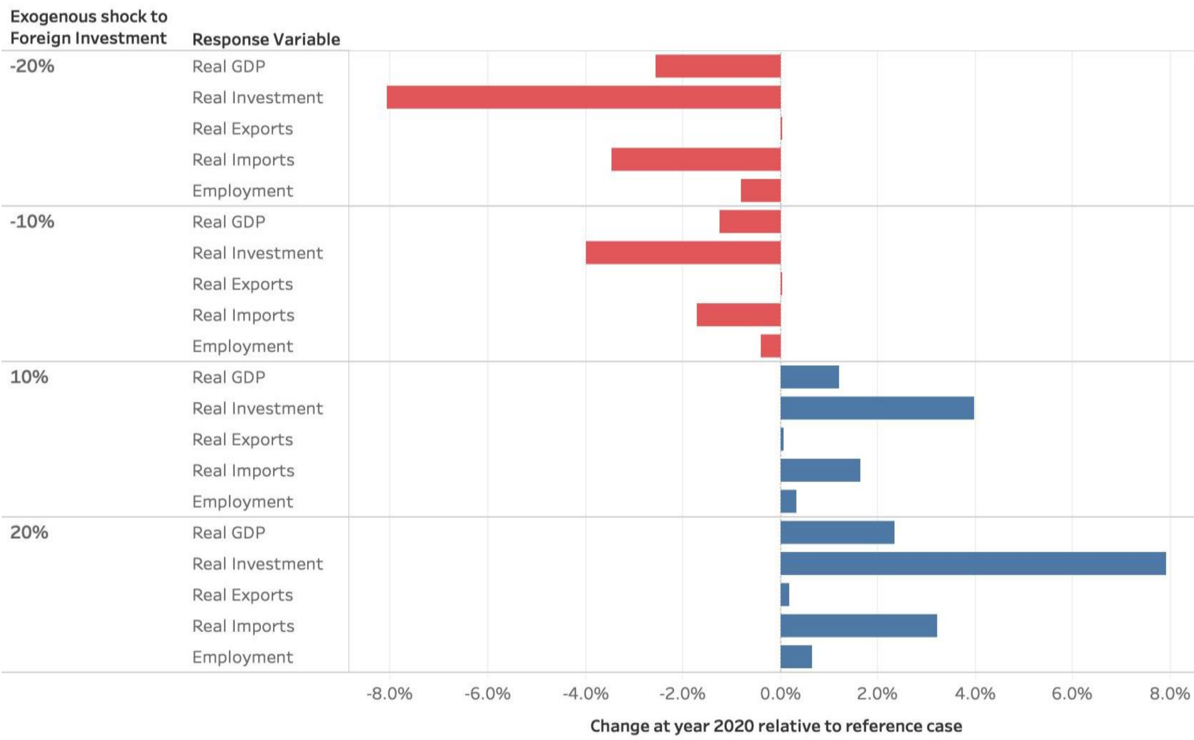
The reports and surveys mentioned above conduct only binary comparisons between “foreign-owned” (i.e. foreign-ownership greater than 50%) and “Australian-owned” (less than 50% foreign-ownership) businesses. They fail to incorporate the time series nature of inward FDI flows and do not give any indication as to the dynamic interactions between macroeconomic variables.

Donovan and Mai (1996) use a multi-region Computable General Equilibrium (CGE) model to demonstrate that increased capital mobility strengthens comparative advantage in capital-intensive sectors such as mining, and thus has a beneficial effect on Australia’s trade balance.

The Department of Treasury (2012) also used a version of the Monash Multi Regional Forecasting (MMRF)[7] dynamic CGE model to simulate the effect of a reduction in net foreign liabilities equal to 1% of GDP. Their simulation found that investment had fallen by 3.1% and GDP by 0.7% after ten years (due to a reduction in the capital stock), while exports increased relative to imports (by identity of the balance of payments).

An Access Economics (2010) report commissioned for the Australian Business Council estimated the impacts of positive and negative shocks to foreign investment inflows using an in-house CGE model. Their results are summarised in **Figure 3a**.

Figure 3a: Projected impacts of shocks to foreign investment, Access Economics CGE model
Source: Access Economics (2010)



Notably, their model shows that a 10% increase in FDI inflows over 2010-2020 is projected to increase real GDP by 1.2% by 2020 relative to the reference case. Their analysis supports the conclusions of Donovan and Mai (1996) in finding that capital-intensive sectors including mining and construction benefitted the most from

[7] For more information on the MMRF model see Adams et al (2010)

increased foreign capital inflows (and therefore reduced capital rents), while exports and employment in the agriculture and manufacturing sectors were projected to decline. Importantly, both the MMRF and Access Economics models are at odds with claims by Donovan and Mai (1996) and DFAT (2018) that foreign investment is favourable for Australia's trade balance.

Although intuitively appealing, these CGE models are far from exact[8] and ignore other possible transmission mechanisms by which FDI may affect the macroeconomy, including firm linkages, knowledge spillovers and other localisation effects discussed extensively in the theoretical literature. They also lump all types of foreign investment inflows together – this is problematic as FDI, portfolio investment, derivatives and other investment (which together make up total foreign investment) are fundamentally different in their nature, flow to different sectors of the economy and are expected to exhibit different behaviours.

Turning to econometric analyses, Layton and Makin (1993) estimate economy-wide Cobb-Douglas and constant elasticity of substitution production functions by ordinary least squares (OLS) using annual data from 1968-1988, and use the results to simulate output and income in the absence of foreign capital inflows (as opposed to FDI). They find that real per capita GDP growth was approximately 15% higher over the period due to foreign capital inflows. This result was supported by Makin (1997) who used a similar technique to show that real national income in Australia had increased by around 5% of 1991/92 GDP due to the foreign capital inflows in the early 1980s.

Boon (2011) performs causality testing on bivariate VECMs and VARs estimated for 18 developed and developing economies over the period 1965-2004. For Australia he finds bi-directional causality between FDI and GFCF, but no long-run causal relationship running from FDI to either GDP or total factor productivity (TFP), concluding that FDI contributes to growth only through the capital accumulation channel.

[8] CGE models are constrained by theoretical assumptions which may not be valid, and are typically calibrated with data from one year, which may cause the models to produce unrealistic results.

As part of Kirchner's (2012) general-to-specific model of the determinants of Australian inward FDI he conducts causality testing to check for endogeneity between FDI and GDP, productivity, portfolio investment and trade openness using quarterly data from 1989-2004. Applying the Toda-Yamamoto (1995) procedure, he finds no evidence for Granger-causality running from FDI to any of the explanatory variables based on lagged levels, though he notes that most of the variables have a contemporaneous relationship with FDI in first differences. Shan and Sun (1998) also apply the Toda-Yamamoto procedure to quarterly Australian inward FDI data from 1970-1996 and find uni-directional causality from FDI to domestic saving. However, these studies offer no insight into the strength or direction of causality, nor any specific estimates of the impacts and dynamic movements of FDI, output and other explanatory variables.

Faeth (2006) remains the only single-country study on the effects Australian inward FDI to use time series econometric modelling. She estimates a multivariate VECM on quarterly FDI data from Q3/1985 to Q2/2002 and applies Granger-causality testing and impulse response analysis, finding that FDI has a significant positive effect on domestic investment and GDP growth. She also finds that FDI decreases export growth in both the short and long-run, and did not have any direct effect on imports, concluding that FDI has an overall negative effect on Australia's trade balance.[9]

[9] This thesis makes an improvement on Faeth's work by using a more robust econometric methodology and conducting additional sensitivity testing on the causal relationships (to be elaborated upon in due course).

4 Data

Apart from the Foreign Investment Review Board (FIRB) – which provides data on foreign investment proposals and approvals (and is thus thought of as a good leading indicator of foreign investment inflows) – the main source of historical FDI data is the Australian Bureau of Statistics (ABS). The ABS publishes FDI flow data in *Catalogue 5302.0 – Balance of Payments and International Investment Position*, which is updated quarterly. For a complete list of all data sources used in this thesis please refer to **Appendix B**.

Quarterly time series data published by the ABS are used throughout this analysis, spanning the period from Q3/1985 to Q2/2019 (a total of 136 observations for each series). Since the ABS definition of FDI changed in June 1985 (when the equity interest threshold for classification as direct investment was lowered from 25% to 10%), the sample for this analysis is restricted to data published after that date.

Data for Gross Domestic Product (GDP), Exports, Imports and Gross Fixed Capital Formation (GFCF)[10] are taken from ABS *Catalogue 5206.0 - National Accounts: National Income, Expenditure and Product.* The data are recorded in real terms (chain volume measures).

Since the ABS produces both seasonally-adjusted[11] and trend estimates[12] for each series, a choice needed to be made regarding which to use. Subsequent time series models estimated using trend estimates showed high degrees of autocorrelation amongst residuals. This is likely caused by the 7-term Henderson moving average being applied uniformly to each series in order to capture the trend. Seasonally-adjusted estimates did not exhibit the same problems with autocorrelation and as such were chosen for the remainder of the analysis.

[10] GFCF (total investment) represents net additions to fixed assets, comprising both foreign and domestic components.
[11] Seasonally-adjusted estimates are produced using the ABS SEASABS software package, which applies the X-11-ARIMA method to remove seasonal and irregular components.
[12] Trend estimates smooth noise from seasonally-adjusted estimates, using a 7-term Henderson moving average for quarterly series. For detail see ABS (2016).

Data for FDI are less straightforward. The ABS does not separately record gross inward FDI flows, but instead reports quarterly flows in the direct investment liabilities account within the financial account of the balance of payments. Consistent with international reporting standards set by the International Monetary Fund (IMF), these data are presented according to directional principle, whereby direct investment inflows are equal to non-resident parents' equity in (and lending to) resident affiliates, minus resident affiliates' equity in (and lending to) foreign parents[13] (IMF 2013, ABS 2016). This national accounting procedure is responsible for producing some negative values in the quarterly FDI series, and thus precludes the use of a logarithmic transformation.

Two outliers in the FDI series were removed and corrected using linear interpolation. These values (a positive inflow of AUD 46.1 billion in Q4/2004 and negative inflow of AUD 50.5 billion in Q2/2005, compared to an average inflow of AUD 7.9 billion per quarter over the sample period) were an accounting anomaly reflecting the impact of the relocation of News Corp headquarters from Australia to the United States (Austrade 2015).[14]

The resulting series was deflated using the implicit price deflator index for GFCF. Because the FDI data are published in their original (not seasonally-adjusted) form, an X-11-ARIMA method was applied to generate seasonally-adjusted estimates[15].

A number of previous studies analysing the effects of FDI on domestic investment calculate the latter by subtracting FDI from gross fixed capital (Faeth 2006, Wang 2010, Morrissey and Udomkerdmongkol 2012) . However, as noted by Jude (2019), this is somewhat inaccurate as FDI inflows do not measure actual spending by foreign firms but are a financial flow on the balance of payments. It is better to use gross fixed capital directly rather than attempting to inaccurately proxy domestic investment.[16]

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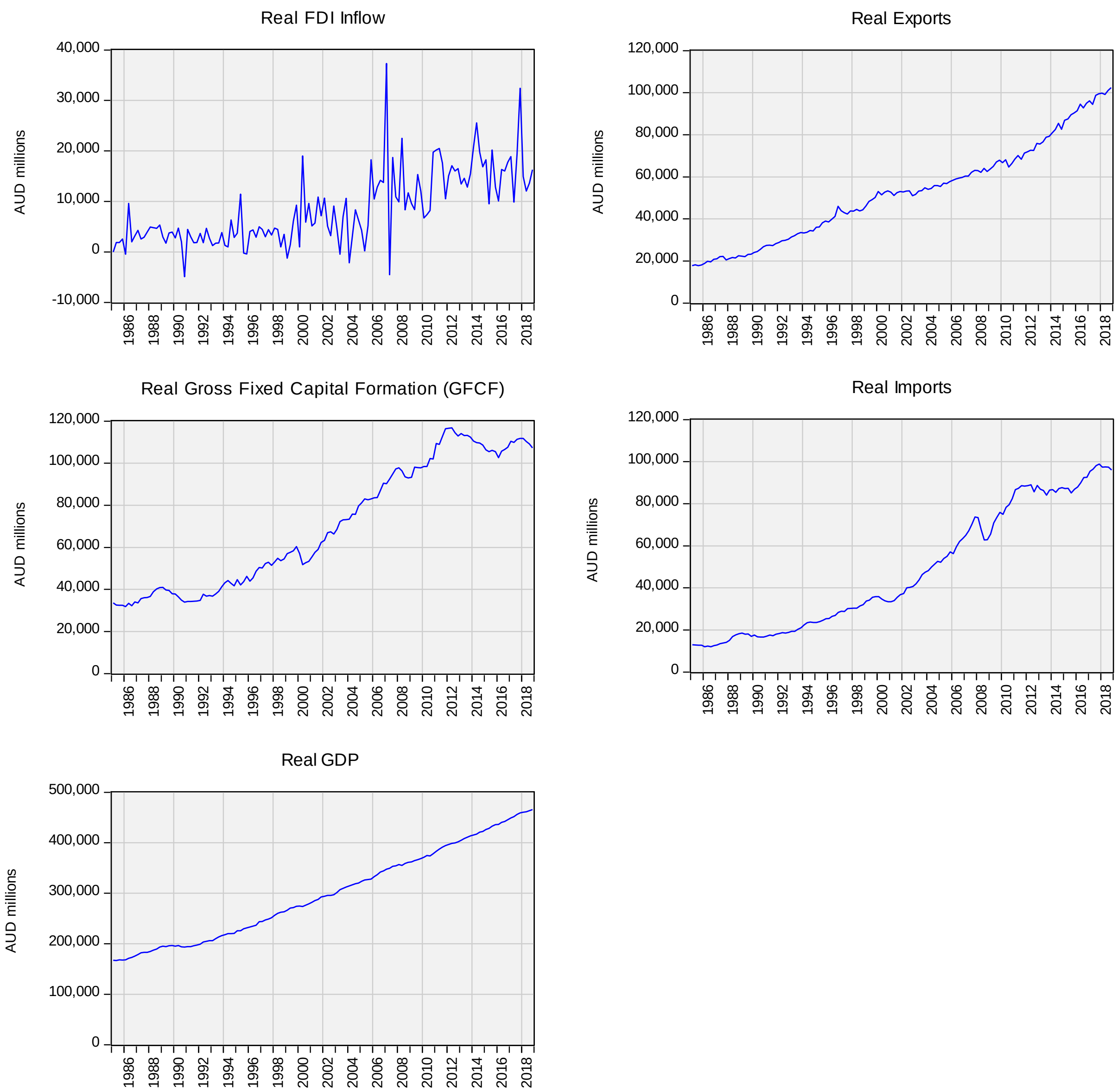
[13] This is also known as reverse investment.
[14] The exact size of the transactions are suppressed by the ABS and the US Bureau of Economic Analysis for commercial confidentiality reasons, so an interpolation was used.
[15] This procedure was applied with the same specifications used by the ABS in ABS (2016).
[16] Information about crowding-out or crowding-in effects of FDI can be gleaned from the size of the coefficient on GFCF relative to that on FDI.

The system under investigation thus contains quarterly, seasonally-adjusted data for the following five real variables:

- Inward foreign direct investment **("FDI")**;
- Exports **("EXP");**
- Gross fixed capital formation **("GFCF");**
- Imports **("IMP"); and**
- Gross domestic product **("GDP")**

Time plots of the five series are shown below.

Figure 4a: **Time plots of real FDI inflow, real exports, real imports, real gross fixed capital formation and real gross domestic product over the period Q3/1985 to Q2/2019.**
Sources: ABS Catalogues 5206.0 and 5302.0



5 Method

The method chosen for this analysis is informed by a number of previous studies outlined in **Section 3.2.4**, in particular Chang (2005), Faeth (2006), Tang et al. (2008) and Guru-Gharana and Adhikari (2011). It adopts a modern time series approach with extensive robustness checks, and considers different approaches based on the order of integration and cointegration amongst variables, as the possibilities are numerous.

The five variables are treated symmetrically and endogenously in a VAR/VECM framework, with the resulting model used to conduct impulse response and variance decomposition analysis. Combining this with the Toda-Yamamoto (1995) procedure for Granger-causality testing, this thesis seeks to determine which relationships are significant, as well as their direction and magnitude. The EViews 10 software package is used throughout.

5.1 Testing for stationarity

As a preliminary step, tests for stationarity are conducted for each time series in levels and first differences in order to verify the order of integration of each series. A time series is said to be integrated of order d, that is, $Y_t \sim I(d)$ if it must be differenced d times to make it stationary.

If non-stationary (i.e. $d > 0$) time series are used in regression analysis, there is a danger of obtaining spurious results, as the least squares estimator does not retain its usual properties and standard inference procedures are unreliable. Although most economic time series are $I(1)$, it is still important to verify this is indeed the case – if any of the series are stationary or trend-stationary in levels (i.e. $I(0)$ processes) or they are integrated of order 2 or higher, this will have important implications for subsequent modelling.

A popular test for determining the stationarity of a time series is the Augmented Dickey-Fuller (ADF) test. Consider a simple autoregressive $AR(1)$ process:

$$y_t = \rho y_{t-1} + \beta' \mathrm{D}_t + \mu_t \tag{5.1}$$

Where:

- $\mathrm{D}_{\boldsymbol{t}}$ contains optional exogeneous regressors such as an intercept, or intercept and deterministic trend;
- ρ and β' are coefficients to be estimated; and
- ε_t is white noise

If $|\rho| \geq 1$ then y_t is non-stationary and is said to possess a unit root[17], as the variance of y_t is increasing with time and approaches infinity. Otherwise, if $|\rho| < 1$ then the series is stationary or trend-stationary. The ADF test equation is specified by subtracting y_{t-1} from both sides of **(5.1)**, and adding lagged first difference terms to allow for the possibility that the error term is autocorrelated, as below:

$$\Delta y_t = \alpha y_{t-1} + \beta' \mathrm{D}_t + \sum_{i=1}^{m} a_i \Delta y_{t-i} + \mu_t \tag{5.2}$$

Where:

- $\alpha = \rho - 1$;
- Δy_{t-i} are lagged first difference terms; and
- a_i are estimated lag coefficients.

The null hypothesis H_0: $\alpha = 0$ (non-stationarity) is then tested against the one-sided alternative hypothesis H_1: $\alpha < 0$ (stationarity or trend-stationarity)[18] with critical values taken from MacKinnon (1996). The test is applied for two separate cases of **(5.2)** – i) where D_t includes an intercept only; and ii) where it includes both an

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[17] It is equivalent to say that a time series has a unit root, it is non-stationary, it has a stochastic trend, or it is integrated of order one or more.
[18] Since $\alpha = \rho - 1$, for stationarity we require $\alpha < 0$.

intercept and deterministic trend.[19] The optimum lag order for the lagged first difference terms is chosen by minimising the value of the Akaike Information Criterion.

There is some evidence in the literature that suggests Dickey-Fuller type tests suffer from low power (Nelson and Plosser 1982, Gujarati 2009) though other studies conclude it performs reasonably well (DeJong et al. 1992). To ensure the stationarity test results are robust, the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test developed by Kwiatkowski et al. (1992) is used in addition to the ADF test. The KPSS statistic is derived from the following model:

$$y_t = r_t + \beta' \mathrm{D}_t + \mu_t \qquad \textbf{(5.3)}$$

Here, r_t is a pure random walk, i.e. $r_t = r_{t-1} + \epsilon_t$ with innovation variance σ_ϵ^2. The KPSS statistic is the Lagrange multiplier (LM) score to test the null hypothesis $H_0: \sigma_\epsilon^2 = 0$ (implying that μ_t is constant and thus y_t is stationary or trend-stationary) against the alternative $H_1: \sigma_\epsilon^2 > 0$ (y_t is non-stationary). It is derived from the residuals of the OLS regression of y_t on the exogeneous regressors D_t.[20]

It is important to note that contrary to most stationarity tests, the null hypothesis under the KPSS test is stationarity, against the alternative of a unit root. Kwiatkowski et al. (1992) note that the KPSS test is intended to complement the ADF test by testing both the unit root null hypothesis and the stationarity null hypothesis. This can help distinguish series that appear to be $I(0)$, $I(1)$ and those that are not sufficiently informative to be able to make a determination.

Like the ADF test, the KPSS test is applied to each time series under two separate sets of assumptions with regard to the underlying data generating process: i) where D_t includes an intercept only; and ii) where it includes both an intercept and deterministic trend.

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[19] Note that the critical values of the test statistics are different for each of the two cases.
[20] The equation for the KPSS test statistic is omitted here for convenience. For more detail see Kwiatkowski et al. (1992) and EViews (2019).

5.2 Model Selection

The results of stationarity testing (and cointegration testing, explained in the next section) will inform the choice of time series model used for subsequent analysis. Four distinct possibilities arise with respect to the order of integration and cointegration of the data, which are considered in turn.

5.2.1 VAR in levels

First, in the unlikely event that all variables are $I(0)$, their short-run dynamics may be represented by an unrestricted levels VAR of order p taking the following form:

$$\boldsymbol{Y}_t = \boldsymbol{C} + \sum_{i=1}^{p} \boldsymbol{A}_i \boldsymbol{Y}_{t-i} + \boldsymbol{\varepsilon}_t \tag{5.4}$$

Where:

- $\boldsymbol{Y}_t$ is a vector containing time series data of the five variables of interest;
- $\boldsymbol{C}$ is a vector of constants (intercepts)
- $\boldsymbol{A}_1 \dots \boldsymbol{A}_p$ are 5×5 matrices of coefficients to be estimated; and
- $\boldsymbol{\varepsilon}_t$ are white-noise disturbances
- The order p denotes the number of lags included for each dependent variable in the model

5.2.2 VAR in first differences

Second, if all the variables are $I(1)$, then equation **(5.4)** may be transformed into a VAR in first differences:

$$\Delta\boldsymbol{Y}_t = \boldsymbol{C} + \sum_{i=1}^{p} \boldsymbol{A}_i \Delta\boldsymbol{Y}_{t-i} + \boldsymbol{\varepsilon}_t \tag{5.5}$$

Where Δ denotes the difference operator. Taking first differences ensures that the conventional asymptotic theory remains valid for hypothesis testing (Sims 1980).

Care must be taken with regards to whether equation (5.4) or (5.5) is used. If there is any reasonable possibility of the data being $I(1)$, estimating a VAR in levels is likely to produce spurious results, even with large samples (Ashley and Verbrugge 2009). On the flipside, estimating a VAR in first differences is dangerous if the data are not truly $I(1)$. Over-differencing not only reduces the efficiency of the regression parameters by reducing sample variability of the regressor, but also runs the risk of increasing the variance of the data and inducing artificial negative autocorrelation (Levendis 2018).

5.2.3 Vector Error Correction Model (VECM)

The third possibility relates to a special case wherein $I(1)$ time series variables share a common stochastic trend(s), such that there exist one or more linear combinations of them that are $I(0)$. In this case the $I(1)$ variables are said to be cointegrated, meaning that they exhibit some kind of long-term equilibrium relationship. Drawing from theoretical arguments presented in the previous section of this thesis, it is expected (though not assumed) that there will be at least one long-run cointegrating relationship between the five variables under investigation. The possibility that there is more than one cointegrating relationship cannot be ruled out.

With cointegration present, subsequent modelling should include an error correction term (ECT) to relate the variables' short-run behaviour to their long-run equilibrium (Gujarati 2009). Ignoring the ECT may give rise to estimation biases and misleading results. Indeed, a system of cointegrated variables does not admit a pure VAR representation in first differences as per equation (5.5), and such a representation would be "throwing away" information about the system's long-run tendencies (Lutkepohl 2005). Instead, the suitable modelling framework is the vector error correction model (VECM), which may be represented as follows for a five-variable system:

$$\Delta \boldsymbol{Y}_t = \boldsymbol{C} + \mathbf{\Pi}\boldsymbol{Y}_{t-1} + \sum_{i=1}^{p-1} \mathbf{\Gamma}_i \Delta \boldsymbol{Y}_{t-i} + \boldsymbol{\varepsilon}_t \qquad \textbf{(5.6)}$$

Where:

- $\mathbf{\Pi}$ is a coefficient matrix, which may be written as $\mathbf{\Pi} = \alpha\beta'$
- $\mathbf{\Pi}$ has rank r, where r denotes the number of cointegrating vectors present in the system[21]
- β is a $5 \times r$ "cointegrating matrix" – its columns contain the r linearly-independent cointegrating vectors among components of $\boldsymbol{Y}_t$
- α is a $5 \times r$ "loading matrix" – its columns contain the r adjustment vectors (effectively the weights attached to each cointegrating vector)[22]
- $\mathbf{\Gamma}_i$ are matrices of coefficients to be estimated – these describe dynamic relationships in the short-run[23]
- The ECT is embedded inside the $\mathbf{\Pi}\boldsymbol{Y}_{t-1}$ term (along with the adjustment parameters), with one ECT for each cointegrating vector

Note that the VECM representation can be obtained from the levels VAR **(5.4)** by subtracting $\boldsymbol{Y}_{t-1}$ from both sides and rearranging, meaning that the VECM is automatically specified in terms of first differences. Supposing there are two cointegrating relations, equation **(5.6)** may be re-written in matrix form as follows:

[21] This result follows from the Granger Representation Theorem of Engle and Granger (1987) and Johansen (1991).
[22] For more on the properties of VECM systems see Enders (2010) and Lutkepohl and Kratzig (2004).
[23] It is also possible to write $\Pi = -(\boldsymbol{I}_K - \mathbf{A}_1 - \cdots - \mathbf{A}_p)$ and $\Gamma_i = -(\mathbf{A}_{i+1} + \cdots + \mathbf{A}_p)$ for $i = 1, \ldots, p-1$

$$\begin{bmatrix} \Delta y_{1,t} \\ \Delta y_{2,t} \\ \Delta y_{3,t} \\ \Delta y_{4,t} \\ \Delta y_{5,t} \end{bmatrix} = \begin{bmatrix} c_1 \\ c_2 \\ c_3 \\ c_4 \\ c_5 \end{bmatrix} + \begin{bmatrix} \alpha_{1,1} & \alpha_{1,2} \\ \alpha_{2,1} & \alpha_{2,2} \\ \alpha_{3,1} & \alpha_{3,2} \\ \alpha_{4,1} & \alpha_{4,2} \\ \alpha_{5,1} & \alpha_{5,2} \end{bmatrix} \begin{bmatrix} \beta_{1,1} & \beta_{1,2} & \beta_{1,3} & \beta_{1,4} & \beta_{1,5} \\ \beta_{2,1} & \beta_{2,2} & \beta_{2,3} & \beta_{2,4} & \beta_{2,5} \end{bmatrix} \begin{bmatrix} y_{1,t-1} \\ y_{2,t-1} \\ y_{3,t-1} \\ y_{4,t-1} \\ y_{5,t-1} \end{bmatrix}$$

$$+ \sum_{i=1}^{p-1} \begin{bmatrix} \Gamma_{11,i} & \cdots & \Gamma_{15,i} \\ \Gamma_{21,i} & \cdots & \Gamma_{25,i} \\ \Gamma_{31,i} & \cdots & \Gamma_{35,i} \\ \Gamma_{41,i} & \cdots & \Gamma_{45,i} \\ \Gamma_{51,i} & \cdots & \Gamma_{55,i} \end{bmatrix} \begin{bmatrix} \Delta y_{1,t-i} \\ \Delta y_{2,t-i} \\ \Delta y_{3,t-i} \\ \Delta y_{4,t-i} \\ \Delta y_{5,t-i} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \\ \varepsilon_{3,t} \\ \varepsilon_{4,t} \\ \varepsilon_{5,t} \end{bmatrix} \qquad (5.7)$$

Where:

- The numerical subscripts $1,2,\ldots,5$ denote the five time series variables under consideration, namely FDI, EXP, IMP, GFCF and GDP;
- The two columns of matrix β represent the coefficients of the two cointegrating equations (note these are rows in the transpose matrix);
- The two columns of matrix α represent the speed of adjustment parameters attached to each cointegrating equation; and
- The rows of matrices β and α correspond to each of the five variables in the system.

In **(5.7)** there are two ECTs (one for each cointegrating equation) which together correct deviations from long-run equilibrium in the previous period. These may be represented as follows:

$$\begin{aligned} ECT_{1,t-1} &= \beta_{1,1} y_{1,t-1} + \beta_{1,2} y_{2,t-1} + \ldots + \beta_{1,5} y_{5,t-1} \\ ECT_{2,t-1} &= \beta_{2,1} y_{1,t-1} + \beta_{2,2} y_{2,t-1} + \ldots + \beta_{2,5} y_{5,t-1} \end{aligned} \qquad (5.8)$$

The ECTs are pre-multiplied by the coefficients of the loading matrix α, which indicate the "speed" at which previous-period deviations are corrected.

In practice some basic extensions may be required to better represent the characteristics of the variables of interest. For example, a deterministic trend is easily incorporated by adding it to the right hand side of **(5.6)**, to give:

$$\Delta \boldsymbol{Y}_t = \boldsymbol{C} + \Pi \boldsymbol{Y}_{t-1} + B\boldsymbol{X}_t + \sum_{i=1}^{p-1} \Gamma_i \Delta \boldsymbol{Y}_{t-i} + \boldsymbol{\varepsilon}_t \tag{5.9}$$

Where $\boldsymbol{X}_t$ a vector of deterministic trend variables and B is a coefficient matrix. Dummies and other exogenous variables may be added in a similar vein.

5.2.4 Structural VECM (SVECM) and Autoregressive Distributed Lag (ARDL)

The fourth possibility arises if one or more of the five variables under investigation is $I(0)$ while the remainder are $I(1)$. If the $I(1)$ variables are cointegrated, it is possible to estimate a structural VECM (SVECM), using identifying restrictions on the coefficients of the matrices α and β to reflect the fact that some series are stationary.

In general, for each $I(0)$ variable in the SVECM there should be a column in matrix β with a unit in the position corresponding to that variable, and zeros elsewhere (Johansen 1995, Lutkepohl 2005). In addition, for each $I(0)$ variable included in the model, there will be an additional cointegrating vector in matrix β, although these additional vectors do not represent cointegration in the traditional sense. They can, however, be accommodated easily in the model for estimation and inference purposes (Lutkepohl and Kratzig 2004).

Another way to deal with mixture of $I(0)$ and $I(1)$ variables is by estimating an autoregressive distributed lag (ARDL) model according to the framework developed by Pesaran and Shin (1995). Unlike the VAR and VECM models discussed previously, ARDL is a single equation framework in which the dependent variable is explained by a combination of its own lags, the explanatory variables, and their lagged values.

Cointegration can be tested in the ARDL framework using the bounds testing approach of Pesaran et al. (2001). If cointegration is detected, an ECT can be added to the short-run model. However, ARDL has drawbacks including that the explanatory variables should be at least weakly exogenous, it cannot detect multiple cointegrating vectors, and it cannot be used to compute impulse responses or forecast error variance decompositions.

The four possibilities discussed above are summarised in the following table along with examples from the empirical FDI literature. Note that none of the representations permit any of the time series to be integrated $I(2)$ or higher[24].

Table 5a: Integration, cointegration and model selection – summary of possible cases

Case	Description	Model Selection	Example
1	All series are I(0)	VAR in levels	Shan (2002)
2	All series are I(1) and there is no cointegration	VAR in first differences	Kim & Seo (2003)
3	All series are I(1) and there is cointegration	VECM	Chang (2005) Tang (2008)
4	There is a mixture of I(0) and I(1) series	SVECM if I(1) variables cointegrated, or ARDL	Faeth (2006) (SVECM) Iqbal (2013) (ARDL)

5.3 Testing for cointegration

Numerous methods for cointegration testing have been proposed in the literature. A simple method developed by Engle and Granger (1987) entails constructing a static OLS regression of the variables under consideration, and concluding in favour of cointegration if the residuals are stationary. However, this single-equation approach has serious limitations, including sensitivity to the choice of dependent variable – in practice it is possible that normalising on one variable ordering indicates cointegration, while normalising on another ordering indicates no cointegration (Enders 2004). Moreover, the Engle-Granger procedure is unable to detect more than one cointegrating relation, which is especially problematic in multivariate

[24] It is unlikely that any of the variables of interest are $I(2)$, and as such time series modelling with $I(2)$ variables is not discussed in this thesis. Most economic and finance variables are $I(1)$.

models where multiple cointegrating vectors can exist (Armstrong 2001). Finally, Engle-Granger is a two-step estimator (since it first generates a residual series and then uses these residuals to estimate another regression) so any biases in the first step are carried forward into the second.

The maximum likelihood systems-based estimation procedure developed by Johansen (1988) and Johansen and Juselius (1990) is a better alternative. It is a one-step procedure, and is able to detect multiple cointegrating relationships. Most importantly, it ensures coefficient estimates are symmetrically distributed and asymptotically efficient, thereby allowing tests of linear restrictions on the cointegrating vectors and speed of adjustment coefficients in **(5.7)**. This is not possible with the Engle-Granger approach. The Johansen procedure has also been found to perform better in Monte Carlo experiments (Gonzalo 1994). Thus, the Johansen procedure is chosen for this analysis.

To illustrate further, consider equation **(5.6)** once more:

$$\Delta\boldsymbol{Y}_t = \boldsymbol{C} + \Pi\boldsymbol{Y}_{t-1} + \sum_{i=1}^{p-1}\Gamma_i\Delta\boldsymbol{Y}_{t-i} + \boldsymbol{\varepsilon}_t$$

The Johansen procedure estimates Π from an unrestricted VAR and tests restrictions under different assumptions related to its rank, r. If $r = 0$ then $\mathbf{\Pi}$ is null and the VECM **(5.6)** reduces to a VAR in first differences **(5.5)**. If $\mathbf{\Pi}$ has full rank (in this case $r = 5$) then the vector process is stationary.

Johansen (1988, 1991) showed that if the matrix $\mathbf{\Pi}$ has reduced rank ($0 < r < 5$), then there exist $5 \times r$ matrices α and β each with rank r such that $\mathbf{\Pi} = \alpha\beta'$. It can then be shown that $\beta'\boldsymbol{Y}_{t-1}$ is stationary, and the columns of matrix β contain r cointegrating vectors. r is thus referred to as the cointegrating rank of the system.[25] The rank of a matrix is equal to the number of its non-zero characteristic roots (eigenvalues). To determine the value of r, it is possible to obtain estimates of the

[25] For a more intuitive proof of this result, see Enders (2010) p.419-424.

characteristic roots of $\mathbf{\Pi}$ and test how many of them are significantly different from zero. This conducted using the trace and maximum eigenvalue statistics given below:[26]

$$\lambda_{trace}(r) = -T \sum_{i=r+1}^{n} \ln(1 - \hat{\lambda}_i) \quad \textbf{(5.10)}$$

$$\lambda_{max}(r, r+1) = -T \ln(1 - \hat{\lambda}_{r+1}) \quad \textbf{(5.11)}$$

Where:

- $\hat{\lambda}_i$ are the estimated values of the characteristic roots obtained from the estimate of $\mathbf{\Pi}$
- T is the number of sample observations

The value of the test statistics will be larger the further the estimated characteristic roots are from zero. For the five-variable system under consideration in this thesis, the trace test proceeds sequentially from $r = 0$ to $r = 4$ until failing to reject the null hypothesis of at most r cointegrating relations. The maximum eigenvalue test tests the null of at most r cointegrating relations against the alternative of $r + 1$. Critical values of both statistics are nonstandard and calculated using Monte Carlo simulations[27].

Before conducting the tests, it is necessary to make an assumption regarding the deterministic trend underlying the data. Typically these are chosen from the five sets of assumptions summarised by Johansen (1995) and presented in **Table 5b**.

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[26] Lutkepohl et al. (2001) find that both tests have similar power. They are both likelihood ratio (LR) tests and differ only slightly in their assumption about the deterministic component of the data generation process.
[27] These are calculated automatically by EViews. Alternatively, tables are provided by Enders (2010) p.492.

Table 5b : Deterministic trend cases for the Johansen cointegration testing procedure			
Case	Trend Assumptions		Test Equation
1	Level data: Cointegrating. Equation:	No deterministic trend No intercept	$\mathbf{\Pi}\boldsymbol{Y}_{t-1} + B\boldsymbol{X}_t = \alpha\beta'\boldsymbol{Y}_{t-1}$
2	Level data: Cointegrating. Equation:	No deterministic trend Intercept only	$\mathbf{\Pi}\boldsymbol{Y}_{t-1} + B\boldsymbol{X}_t = \alpha(\beta'\boldsymbol{Y}_{t-1} + \rho_0)$
3	Level data: Cointegrating. Equation:	Linear trend Intercept only	$\mathbf{\Pi}\boldsymbol{Y}_{t-1} + B\boldsymbol{X}_t = \alpha(\beta'\boldsymbol{Y}_{t-1} + \rho_0) + \alpha_\perp\gamma_0$
4	Level data: Cointegrating. Equation:	Linear trend Linear trend & intercept	$\mathbf{\Pi}\boldsymbol{Y}_{t-1} + B\boldsymbol{X}_t = \alpha(\beta'\boldsymbol{Y}_{t-1} + \rho_0 + \rho_1 t) + \alpha_\perp\gamma_0$
5	Level data: Cointegrating. Equation:	Quadratic trend Linear trend & intercept	$\mathbf{\Pi}\boldsymbol{Y}_{t-1} + B\boldsymbol{X}_t = \alpha(\beta'\boldsymbol{Y}_{t-1} + \rho_0 + \rho_1 t) + \alpha_\perp(\gamma_0 + \gamma_1 t)$

Note: $\alpha_\perp\gamma_0$ is the deterministic trend term outside the cointegrating relation, and $\rho_1 t$ is the deterministic trend term inside it.[28] The term $\alpha_\perp$ describes the null space of α such that $\alpha'\alpha_\perp = 0$. ρ_0 and ρ_1 are vectors of coefficients.

Time plots in **Figure 3a** strongly suggest the presence of linear trends in the level series, but it is not known whether these are deterministic or stochastic. This analysis proceeds according to the recommendations of Johansen (1995) and EViews (2019). Case (3) should be used if the trends in the level series are found to be stochastic in nature, while case (4) should be used if any of the series are believed to contain deterministic trends.

It is also necessary to choose the appropriate lag order to include in the Johansen testing procedure. As is standard practice in the empirical literature, this is selected by estimating an unrestricted VAR in levels and choosing the lag order which minimises the value of some information criterion, and ensures that the residuals are free of autocorrelation. The Akaike Information Criterion and Schwarz Information Criterion are most commonly used[29]. For this analysis, the Akaike Information Criterion was chosen as Monte Carlo simulations have shown it has better small sample properties, and errs on the side of caution by favouring over- rather than under-parameterised models (Enders 2010). However, since Gonzalo (1994) finds that the Johansen procedure is quite sensitive to the chosen lag order, the tests are re-run with alternative lag orders to ensure the results are robust.

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[28] The decomposition of the trend between the inside and outside of the cointegrating relation is not uniquely identified. EViews identifies it by forcing the ECT to have a sample mean of zero. For more detail see EViews (2019).
[29] Final Predication Error (FPE) or the Hannan Quinn Criterion (HQ) are also used occasionally.

If the Johansen procedure indicates the existence of one or more cointegrating vectors, a VECM or SVECM may be estimated, otherwise a VAR or ARDL framework may be used instead (see **Section 5.2** and **Table 5a**).

5.4 The Toda-Yamamoto approach to Granger-causality

Once the VAR or VECM model is estimated in its unrestricted form, it is desirable to test for Granger-causality amongst the variables in the system. This will also help in forming hypotheses which can then be tested in the cointegration space, which is discussed further in the next section.

The most common approach to causality testing is based on the work of Granger (1969). In particular, x is said to Granger-cause y if y can be better predicted using past information about both x and y, than it can with only past information about y. Consider the following two-variable VAR system:

$$\begin{aligned} y_t &= \mathrm{c}_1 + \sum_{i=1}^{p} \alpha_i y_{t-i} + \sum_{i=1}^{p} \beta_i x_{t-i} + \varepsilon_{1t} \\ x_t &= \mathrm{c}_2 + \sum_{i=1}^{p} \gamma_i y_{t-i} + \sum_{i=1}^{p} \delta_i x_{t-i} + \varepsilon_{2t} \end{aligned} \qquad \mathbf{(5.12)}$$

Rejecting the null hypothesis $H_0 : \beta_1 = \beta_2 = \ldots = \beta_p = 0$ indicates that x Granger-causes y, while rejecting $H_0 : \gamma_1 = \gamma_2 = \ldots = \gamma_p = 0$ is evidence that y Granger-causes x.

However, using the typical Wald coefficient restriction test on the parameters of a VAR or VECM with non-stationary data produces a test statistic that does not retain its usual asymptotic chi-square distribution under the null hypothesis (Lutkepohl 2005). This means that traditional *F*-test statistics are invalid if the data are non-stationary and should not be used for Granger-causality analysis (Toda and Yamamoto 1995).

Toda and Yamamoto (1995) suggest a procedure to address this shortcoming. They set up the following over-fitted levels VAR($k + d_{\max}$) model:

$$Y_t = \boldsymbol{C} + \sum_{i=1}^{k} \boldsymbol{A}_i \boldsymbol{Y}_{t-i} + \sum_{j=k+1}^{d_{\max}} \boldsymbol{A}_j \boldsymbol{Y}_{t-j} + \varepsilon_t \tag{5.13}$$

Where:

- k is the system's usual lag length, most commonly selected using the Akaike Information Criterion, Schwarz Information Criterion and/or other information criteria; and
- $d_{\max}$ is the maximum order of integration within the system.

To maintain an asymptotic chi-square distribution of the text statistic, the procedure utilises a modified Wald (MWald) test – that is, it applies standard Wald tests to the first k coefficient matrices but ignores the $d_{\max}$ coefficient matrices (essentially treating the extra $d_{\max}$ lags as exogenous to correct the asymptotics).

The over-fitted Toda-Yamamoto VAR is robust to a wide range of systems including stationary, integrated, fractionally-integrated and mixed integrated and stationary systems, and may be applied to both cointegrated and non-cointegrated data (Giles and Williams 2000). Moreover, it typically has higher power compared to alternative procedures, especially when the sample size is small (Yamada and Toda 1998).

5.5 Hypothesis testing and model restrictions

As noted in **Section 5.3**, the Johansen procedure allows for the testing of restrictions on the individual cointegrating vectors (coefficients of the cointegrating matrix β) and/or speed of adjustment parameters (coefficients of the loading matrix α).[30] Hence these restrictions are effectively hypothesis tests on the form of the long-run relationship between the variables. Hypothesised restrictions can be informed by economic theory as well as statistical methods. In this case, both the theoretical FDI

[30] Note that α and β are not uniquely identified.

literature and the Toda-Yamamoto Granger-causality test results may be drawn upon to identify meaningful restrictions, which can be subsequently tested.

Importantly, if there are r cointegrating vectors, then only these r linear combinations of the variables are $I(0)$, and all other linear combinations are $I(1)$ (Johansen and Juselius 1990). Therefore, restrictions on $\mathbf{\Pi}$ are binding and should be rejected if the estimated number of cointegrating vectors in the restricted system is statistically different from r. This is easily tested by calculating the following LR test statistic:

$$LR = T \sum_{i=r+1}^{n} \left[\ln(1 - \hat{\lambda}_i^*) - \ln(1 - \hat{\lambda}_i) \right] \qquad \textbf{(5.14)}$$

Where $\hat{\lambda}_i^*$ and $\hat{\lambda}_i$ denote the characteristic roots of the restricted and unrestricted models respectively. This test statistic has an asymptotic chi-square distribution with degrees of freedom equal to the number of restrictions imposed, and may be compared with appropriate critical values. If the values of $\hat{\lambda}_i^*$ and $\hat{\lambda}_i$ are very different from one another, this implies that the number of cointegrating vectors has changed, and the null hypothesis containing the restriction is rejected (Enders 2010).

Restrictions can be implemented sequentially and jointly tested using **(5.14)** to verify that they are jointly non-binding. Since VARs and VECMs often contain a large number of parameters, it is usually desirable to impose restrictions in order to reduce the dimensionality of the parameter space and improve estimation precision (Lutkepohl and Kratzig 2004).

It is particularly useful to know whether any of the variables in the system are weakly exogenous, that is, whether they respond to deviations from long-run equilibrium. In practice, testing a variable for weak exogeneity amounts to an LR-test **(5.14)** of the null hypothesis that coefficients in the loading matrix α corresponding to that variable are jointly equal to zero. If the null hypothesis is not rejected, the variable is said to be weakly exogenous, meaning it does not respond to deviations from long-run equilibrium.[31]

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[31] See Engle et al (1983) for further detail on weak exogeneity.

5.6 Diagnostic testing

In order to assess whether the VAR/VECM model accurately represents the underlying data-generating processes, it is necessary to check for defects such as residual autocorrelation, heteroskedasticity and structural instability.

To test for residual autocorrelation at lags 1 to h, an LM test of the type described by Godfrey (1988) is used. The following auxiliary regression is estimated for the VECM residuals using OLS:

$$\hat{\varepsilon}_t = \boldsymbol{C} + \boldsymbol{\Pi Y}_{t-1} + \sum_{i=1}^{p-1} \boldsymbol{\Gamma}_i \Delta \boldsymbol{Y}_{t-i} + B_1 \hat{\varepsilon}_{t-1} + \ldots + B_h \hat{\varepsilon}_{t-h} + e_t \qquad \textbf{(5.15)}$$

And the null hypothesis $B_1 = \ldots = B_h = 0$ is tested against the alternative $B_1 \neq 0 \text{ or} \ldots \text{or } B_h = 0$. Equation **(5.15)** is estimated with and without the lagged residuals $\hat{\varepsilon}_{t-i}$ $(i = 1,2\ldots,h)$. From the estimated residuals $\hat{e}_t$ $(t = 1,2,\ldots,T)$ covariance matrix estimators $\tilde{\Sigma}_e$ and $\tilde{\Sigma}_R$ are obtained for the auxiliary models with and without the lagged residuals, respectively. The LM statistic then compares the two:

$$LM_h = T(K - \mathrm{tr}(\tilde{\Sigma}_e, \tilde{\Sigma}_R)) \qquad \textbf{(5.16)}$$

Under the null hypothesis of no autocorrelation the LM statistic has an asymptotic Chi-square distribution with hK^2 degrees of freedom.[32]

It is also useful to check for signs of residual heteroskedasticity using a systems-based extension of the White (1980) test. Cross products of the residuals are regressed on the cross products of the regressors, and their significance jointly tested using an LM-test.

An examination of the AR roots can verify whether the model is stable. For a K-variable VECM with cointegrating rank r to be stable, the inverse roots of its AR

[32] Both the likelihood ratio (LR) version of the LM-test described by Johansen (1995), as well as the modified *F*-test of Edgerton and Shukur (1999) are reported.

characteristic polynomial should all lie within the unit circle, except for $K - r$ roots which should equal one[33]. If the VECM is not stable, results from the impulse response analysis and FEVD may be invalid (Lutkepohl 2005).

As discussed previously, the VECM estimates may be sensitive to the number of lags included in the system. To ensure the lag order is selected appropriately, it is possible to carry out tests on the significance of the i-th lag in each equation of the model, and the joint significance of the i-th lag of all variables. These are carried out as Wald coefficient restriction tests and the Wald statistic is assumed to have its usual asymptotic chi-square distribution under the null[34]. If the null hypothesis for the joint test (i.e. that all coefficients at the i-th lag are zero) is not rejected this is evidence that a smaller number of lags should be used.

5.7 Impulse response and variance decomposition analysis

Once the VECM has been estimated with the appropriate identifying restrictions, it can be inverted into a vector moving average (VMA) representation. From this representation it is possible to derive impulse response functions which trace the time path of various shocks on the variables in the system (Sims 1980). These can be thought of as the outcome of a hypothetical experiment in which a vector of shocks of magnitude $\boldsymbol{\delta}$ hitting the system at time t is compared with a base case at time $t + n$, given the system's known history (Pesaran and Shin 1998).

[33] See Lutkepohl (2005) for details.
[34] As discussed subsequently, this may not actually be the case if data is non-stationary – the lag exclusion Wald tests are therefore only a rough approximation.

To illustrate this, the K-variable VAR of order p in **(5.4)** is re-written in VMA form:

$$\boldsymbol{Y}_t = \sum_{i=0}^{\infty} \boldsymbol{\Phi}_i \boldsymbol{\varepsilon}_{t-i} \tag{5.17}$$

Where:

- $\boldsymbol{\Phi}_i$ are coefficient matrices;
- $\boldsymbol{\Phi}_0$ is a $K \times K$ identity matrix;
- $\boldsymbol{\varepsilon}_{t-i}$ is a vector of white noise disturbances;
- $E(\boldsymbol{\varepsilon}_t, \boldsymbol{\varepsilon}_s) = \boldsymbol{\Sigma}$ for all t and $E(\boldsymbol{\varepsilon}_t, \boldsymbol{\varepsilon}_s) = 0$ for $t = s$
- $\boldsymbol{\Sigma}$ is a positive, definite covariance matrix $\boldsymbol{\Sigma} = [\sigma_{ij}, i, j = 1,2, \ldots K]$

The $\boldsymbol{\Phi}_i$ matrices in **(5.17)** are calculated according to the following recursive relation:

$$\boldsymbol{\Phi}_i = \boldsymbol{A_i}\boldsymbol{\Phi}_{i-1} + \boldsymbol{A_2}\boldsymbol{\Phi}_{i-2} + \ldots + \boldsymbol{A_p}\boldsymbol{\Phi}_{i-p}, \qquad i = 1,2,3\ldots, \tag{5.18}$$

Since an estimated VAR is under-identified, imposing some structure is necessary in order to identify the impulse response functions. A common way to do this is to choose the magnitude $\boldsymbol{\delta}$ of the shocks using a Cholesky decomposition of $\boldsymbol{\Sigma}$, that is, by choosing some lower triangular matrix $\boldsymbol{P}$ with positive diagonal elements and setting $\boldsymbol{P}\boldsymbol{P}' = \boldsymbol{\Sigma}$. It is then possible to write **(5.17)** in the following way:

$$\boldsymbol{Y}_t = \sum_{i=0}^{\infty} (\boldsymbol{\Phi}_i \boldsymbol{P}) \boldsymbol{\xi}_{t-i} \tag{5.19}$$

Such that the $\boldsymbol{\xi}_t = \boldsymbol{P}^{-1}\boldsymbol{\varepsilon}_t$ are orthogonalised[35]. Orthogonalised impulses of a one-unit shock to the j-th equation on $\boldsymbol{Y}_{t+n}$ can be represented as:

$$\psi_j(n) = \boldsymbol{\Phi}_n \boldsymbol{P} \boldsymbol{e}_j, \qquad n = 0,1,2\ldots, \tag{5.20}$$

[35]In other words, $E(\boldsymbol{\xi}_t, \boldsymbol{\xi}_s)$ is an identity matrix.

Where $\boldsymbol{e}_j$ is a $K \times 1$ selection vector with its j-th element equal to one and zeros in all other positions.[36] The orthogonalised impulses do have the unfortunate side-effect that they are sensitive to the ordering of variables, since the matrix $\boldsymbol{P}$ is lower triangular. The importance of ordering is dependent on the extent of correlation between the residuals (Enders 2010).

To illustrate the implications of this, suppose the variables are ordered y_1, y_2, y_3, y_4, y_5. Then, shocks to y_1 are assumed to disturb all variables contemporaneously; a shock to y_2 will only contemporaneously affect y_2, y_3, y_4 and y_5; and so on. A shock to y_5 will not contemporaneously affect any of the variables prior to it in the ordering.

Therefore, following the method of Sims (1980) and Chang (2005), the presumably exogenous variables are ordered first, followed by the relatively more endogenous variables. Both the weak exogeneity test results and *a priori* information may be used to assist with variable ordering, and alternative orderings may be checked to ensure results are robust. Once generated, the orthogonalised impulse responses are used to examine short-run (1 to 4 quarters) and long-run (up to 24 quarters) relationships between the variables in the system.

Another related tool in time series analysis is the forecast error variance decomposition (FEVD), which reveals the proportion of movements in a variable attributable to its own shocks versus shocks to other variables in the system (Enders 2010). Orthogonalised FEVDs are also calculated using a Cholesky decomposition and may be represented as follows:

$$\theta_{ij}(n) = \frac{\sum_{l=0}^{n}\left(\boldsymbol{e}'_i \boldsymbol{\Phi}_l P e_j\right)^2}{\sum_{l=0}^{n}\left(\boldsymbol{e}'_i \boldsymbol{\Phi}_l \Sigma \boldsymbol{\Phi}'_l e_i\right)} \qquad \textbf{(5.21)}$$

Where $\theta_{ij}(n)$ represents the proportion of the mean squared error (forecast error variance) of variable i attributable to shocks in variable j at time $t+n$ (Lutkepohl

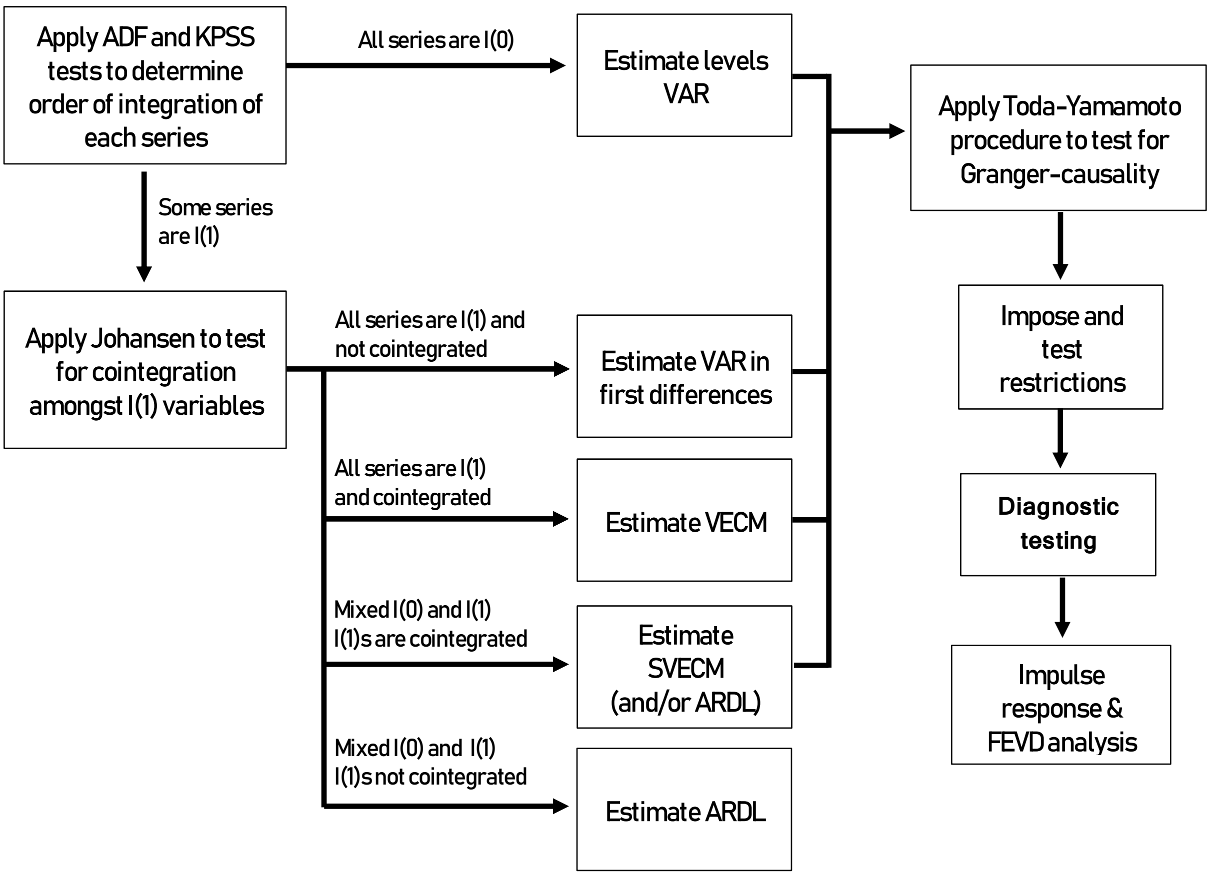
[36] This representation follows Pesaran and Shin (1998). An alternative representation is offered by Lutkepohl (1990).

1990). If shocks in variable j explain none or very little of the forecast error variance of variable i then this implies that y_i is exogenous and evolves independently of the shocks in y_j. The proportion of variable i's forecast error variance attributable to its own shocks usually decreases with time, as the shocks to variable j begin to affect lagged values of variable i. Like the impulse responses, FEVD results are also sensitive to the variable ordering within the VAR. Thus, different orderings are checked to ensure the results are robust.

5.8 Method summary

The method for this analysis can be visualised in the flow diagram below.

Figure 5a: Method selection for time series data in this thesis



6 Results and Discussion

Results are now presented following the “roadmap” set out in **Figure 5a** and methods detailed in **Section 5**. After conducting tests for stationarity and cointegration rank, an unrestricted VECM is estimated and Granger-causality tests are conducted. Following this, hypothesis tests are carried out for restrictions in the cointegrating space, and impulse responses and forecast error variances computed from the restricted model. Finally, the results are examined in detail and extensions are explored with the help of further Granger-causality tests.

6.1 Tests for stationarity

As noted in **Section 5.2**, the appropriate choice of model depends on the order of integration of each time series. The results of the ADF unit root tests and KPSS stationarity tests are shown in **Table 6a** and **Table 6b**.

Table 6a: Augmented Dickey-Fuller test results for FDI, EXP, GFCF, IMP and GDP

Test for unit root in	Levels	Levels	First Differences	First Differences
Test equation specification	Intercept only	Intercept and Trend	Intercept only	Intercept and Trend
Variable	Probability	Probability	Probability	Probability
FDI	0.572	0.109	0.000***	0.000***
EXP	0.999	0.988	0.215	0.041**
GFCF	0.917	0.833	0.000***	0.000***
IMP	0.975	0.506	0.000***	0.000***
GDP	1.000	0.357	0.108	0.000***

Note: Each time series contains 136 quarterly observations over the period September 1985 to June 2019. The null hypothesis of a unit root is tested against the alternative of no unit root for data in levels and first differences, with and without a trend term. Lag length selection is based on the Akaike Information Criterion. MacKinnon (1996) one-sided p-values are reported. *, **, *** denote rejection at the 10%, 5% and 1% level respectively.

Table 6b: Kwiatkowski–Phillips–Schmidt–Shin test results for FDI, EXP, GFCF, IMP and GDP				
Test for unit root in	Levels	Levels	First Differences	First Differences
Test equation specification	Intercept only	Intercept and Trend	Intercept only	Intercept and Trend
Variable	LM-Statistic	LM-Statistic	LM-Statistic	LM-Statistic
FDI	1.290***	0.215**	0.089	0.089
EXP	1.426***	0.200**	0.564**	0.104
GFCF	1.415***	0.185**	0.172	0.110
IMP	1.423***	0.282***	0.220	0.101
GDP	1.460***	0.304***	0.848***	0.096

Note: Each time series contains 136 quarterly observations over the period September 1985 to June 2019. The null hypothesis of stationarity is tested against the alternative of a unit root for data in levels and first differences, with and without a trend term. Newey-West bandwidth is determined automatically using Bartlett kernel. *, **, *** denote rejection at the 10%, 5% and 1% level respectively.

Results of both tests are in agreement - for all five time series in levels, the ADF null hypothesis of a unit root is not rejected, and the KPSS null hypothesis of stationarity is rejected (for both intercept only, and intercept and trend specifications). Thus all five variables are non-stationary in levels. In first differences, the ADF null hypothesis of a unit root is rejected, and the KPSS null hypothesis of stationarity is not rejected, for FDI, IMP and GFCF under the intercept only specification, and for EXP and GDP under the intercept and trend specification. Thus FDI, IMP and GFCF and stationary and EXP and GDP are trend-stationary in first differences, implying all five series are $I(1)$.

6.2 Tests for cointegration

Having confirmed that all five series are $I(1)$, it is necessary to test for cointegration using the Johansen procedure described in **Section 5.3**. Since EXP and GDP were found to contain deterministic trends in first differences, a linear deterministic trend in both the levels data and cointegrating equation is assumed, corresponding to case (4) in **Table 5b**. This follows the recommendation of Johansen (1995). The optimal lag order was chosen as 4 (in differences) by minimising the Akaike Information Criterion in an unrestricted VAR. For both the trace and maximum eigenvalue tests, the null hypothesis of at most 1 cointegrating equations is rejected at the 5% level of significance. This implies that there are two cointegrating equations in the model describing long-run structural relationships between the variables $(r = 2)$. Test results are shown in **Table 6c.**

Table 6c: Johansen cointegration rank test results for FDI, EXP, GFCF, IMP and GDP, assuming a linear deterministic trend in level data and cointegrating equation					
No. of CE(s) under the null	Characteristic Root	Trace test		Maximum eigenvalue test	
		Test statistic	Probability	Test statistic	Probability
None	0.318	100.976	0.000***	50.155	0.000***
At most 1	0.200	50.821	0.026**	29.198	0.031**
At most 2	0.090	21.624	0.320	12.299	0.519
At most 3	0.058	9.325	0.336	7.783	0.401
At most 4	0.012	1.541	0.214	1.541	0.214

MacKinnon-Haug-Michelis (1999) p-values are reported. **, *** denote rejection at the 5% and 1% level respectively. CE means cointegrating equation (i.e. cointegrating vector).

The data were also tested under the more restrictive assumption of case (3) in **Table 5b**, under which the cointegrating equation does not contain a trend. Sensitivity to varying lag orders (3, 4, 5 and 6 lags) was also checked. In all cases, the trace and maximum eigenvalue tests showed that the system contained two cointegrating equations at the 5% level of significance.

Having confirmed that the variables are $I(1)$ and cointegrated, the appropriate modelling framework is a VECM as described in **Section 5.2.3**. Since it is known that the VECM system has cointegrating rank $r = 2$, it is useful to represent it in matrix form by substituting the five variables into equation **(5.7)** to yield:

$$\begin{bmatrix} \Delta FDI_t \\ \Delta EXP_t \\ \Delta GFCF_t \\ \Delta IMP_t \\ \Delta GDP_t \end{bmatrix} = \begin{bmatrix} c_{FDI} \\ c_{EXP} \\ c_{GFCF} \\ c_{IMP} \\ c_{GDP} \end{bmatrix} + \begin{bmatrix} \alpha_{FDI,1} & \alpha_{FDI,2} \\ \alpha_{EXP,1} & \alpha_{EXP,2} \\ \alpha_{GFCF,1} & \alpha_{GFCF,2} \\ \alpha_{IMP,1} & \alpha_{IMP,2} \\ \alpha_{GDP,1} & \alpha_{GDP,2} \end{bmatrix} \begin{bmatrix} \beta_{1,FDI} & \beta_{1,EXP} & \beta_{1,GFCF} & \beta_{1,IMP} & \beta_{1,GDP} \\ \beta_{2,FDI} & \beta_{2,EXP} & \beta_{2,GFCF} & \beta_{2,IMP} & \beta_{2,GDP} \end{bmatrix} \begin{bmatrix} FDI_{t-1} \\ EXP_{t-1} \\ GFCF_{t-1} \\ IMP_{t-1} \\ GDP_{t-1} \end{bmatrix}$$

$$+ \sum_{i=1}^{p-1} \begin{bmatrix} \Gamma_{FDI,1,i} & \cdots & \Gamma_{FDI,5,i} \\ \Gamma_{EXP,1,i} & \cdots & \Gamma_{EXP,5,i} \\ \Gamma_{GFCF,1,i} & \cdots & \Gamma_{GFCF,5,i} \\ \Gamma_{IMP,1,i} & \cdots & \Gamma_{IMP,5,i} \\ \Gamma_{GDP,1,i} & \cdots & \Gamma_{GDP,5,i} \end{bmatrix} \begin{bmatrix} \Delta FDI_{t-i} \\ \Delta EXP_{t-i} \\ \Delta GFCF_{t-i} \\ \Delta IMP_{4,t-i} \\ \Delta GDP_{5,t-i} \end{bmatrix} + \begin{bmatrix} \varepsilon_{FDI,t} \\ \varepsilon_{EXP,t} \\ \varepsilon_{GFCF,t} \\ \varepsilon_{IMP,t} \\ \varepsilon_{GDP,t} \end{bmatrix} \quad \textbf{(6.1)}$$

It is now easy to visualise the two cointegrating vectors (rows of β'); the speed of adjustment coefficients for each cointegrating vector (columns of α); and the short-run coefficients attached to lagged values of each variable (the Γ matrices). Using knowledge that the system's cointegrating rank $r = 2$, equation **(6.1)** can be estimated in its unrestricted form. Unrestricted estimates for coefficients of α and β along with corresponding t-statistics are shown in **Appendix C**.

6.3 Tests for Granger-causality using the Toda-Yamamoto procedure

Before proceeding to test restrictions in the cointegrating space using the VECM, it is useful to gain an understanding of the causal linkages present within the system. As such, the Toda-Yamamoto (1995) procedure is employed to examine Granger-causality running between the five variables: FDI, EXP, GFCF, IMP and GDP.

The over-fitted VAR$(k + d_{\max})$ model is set up according to equation **(5.13)**. The system's usual lag order is chosen as $k = 5$ so as to minimise the value of the Akaike Information Criterion. This was also smallest lag order that ensured the residuals were free of autocorrelation. The lag order $d_{\max}$ was chosen as 1 since the maximum order of integration amongst the five series was 1. Pairwise Granger-causality test results are reported in **Table 6d**.

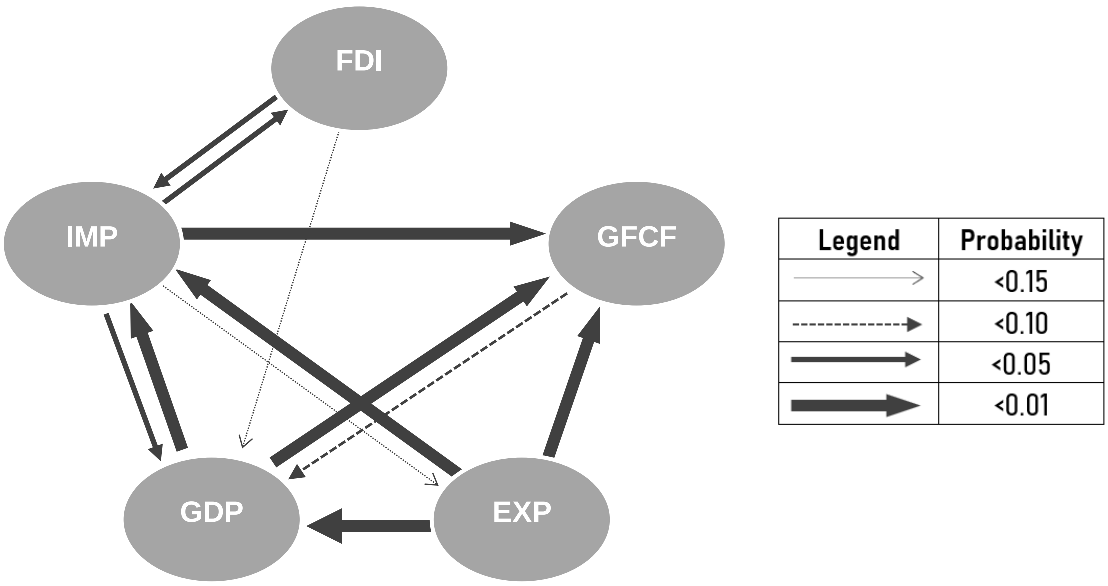
Table 6d: Pairwise Granger-causality test results for FDI, exports, imports, GFCF and GDP using the Toda-Yamamoto modified Wald test

Null hypothesis			MWald Statistic	Probability
EXP	does not Granger cause	FDI	5.429	0.366
GFCF	does not Granger cause	FDI	1.096	0.955
IMP	does not Granger cause	FDI	12.252	0.032**
GDP	does not Granger cause	FDI	3.214	0.667
FDI	does not Granger cause	EXP	2.279	0.809
GFCF	does not Granger cause	EXP	7.090	0.214
IMP	does not Granger cause	EXP	8.783	0.118
GDP	does not Granger cause	EXP	4.205	0.520
FDI	does not Granger cause	GFCF	2.035	0.844
EXP	does not Granger cause	GFCF	25.744	0.000***
IMP	does not Granger cause	GFCF	15.416	0.009***
GDP	does not Granger cause	GFCF	21.014	0.001***
FDI	does not Granger cause	IMP	11.629	0.040**
EXP	does not Granger cause	IMP	20.852	0.001***
GFCF	does not Granger cause	IMP	7.237	0.204
GDP	does not Granger cause	IMP	16.829	0.005***
FDI	does not Granger cause	GDP	8.161	0.148
EXP	does not Granger cause	GDP	24.033	0.000***
GFCF	does not Granger cause	GDP	9.849	0.080*
IMP	does not Granger cause	GDP	12.767	0.026**

Note: results were robust to different choices of the lag order k. *, **, *** denote rejection at the 10%, 5% and 1% level respectively. Note that the null hypotheses "IMP does not Granger cause EXP" and "FDI does not Granger cause GDP" were both rejected at the 15% level of significance.

At first glance the results are surprising. At the 1% level of significance, Granger-causality was detected running from EXP to GFCF, IMP to GFCF, GDP to GFCF, EXP to IMP, and GDP to IMP. At the 5% level, Granger-causality was detected running from IMP to FDI, FDI to IMP, and IMP to GDP. At the 10% level, Granger-causality was found running from GFCF to GDP. Finally, at the 15% level of significance, (very weak) Granger-causality was detected running from FDI to GDP, and IMP to EXP. The null hypothesis of Granger non-causality was not rejected at any meaningful level of significance for any of the other pairwise tests. The causal links may be visualised in the diagram below:

Figure 6a: **Granger-causal links between FDI, EXP, GFCF, IMP and GDP using the Toda-Yamamoto modified Wald test**



No causal relationships were detected between FDI and GFCF, nor FDI and EXP. Surprisingly, the results show evidence for bi-directional causality between FDI and IMP at the 5% level of significance. This is contrary to the findings of Faeth (2006) who finds no causal relationship between FDI and imports in the case of Australia.[37]

[37] However, Faeth (2006) uses joint F-tests which are shown to be invalid by Toda and Yamamoto (1995) for the case of non-stationary data.

The results indicate only very weak evidence that FDI has any direct effect on economic growth. Moreover, there is no evidence to suggest that FDI has a direct effect on GFCF. These findings are at odds with most theoretical and empirical work on the subject and are somewhat surprising.

In theory, FDI is expected to cause both GFCF and GDP (through capital accumulation and technological spillovers). In the case of Australia, it is also plausible to expect FDI to Granger-cause exports, as between 30% to 40% of inward FDI flows to the mining industry (extraction of raw materials for export). None of these expected causal links are detected in the Granger-causality analysis above.

Although the findings are unexpected, they are not totally inconsistent with other evidence in the FDI literature. Ericsson and Irandoust (2001) find no causal link between FDI and GDP in Denmark and Finland. De Mello (1999) finds very weak evidence for the impact of FDI on growth, and no evidence for the impact of FDI on capital accumulation in OECD countries from 1970-1990. Indeed, for the case of Australia over the period 1989-2004, Kirchner (2012) finds no Granger-causality running from FDI to gross domestic income (GDI) nor productivity.

However, FDI seems to have an indirect (two-step Granger-causal) effect on GFCF and GDP by affecting imports. The next part of the analysis will investigate these causal links more closely by utilising the VECM that was constructed earlier.

6.4 Tests for weak exogeneity

The results of these tests are given in **Appendix D**, and show weak exogeneity is rejected for all five variables at the 10% level of significance, and rejected for FDI, GFCF, IMP and GDP at the 1% level. This is a good indication of endogeneity amongst all the variables in the system, consistent with Granger-causality tests[38] conducted in **Section 6.3.**

[38] Rejection of weak exogeneity implies a rejection of Granger non-causality.

6.5 Hypothesis tests on the cointegrating vectors

In addition to testing for weak exogeneity, tests on the form of the cointegrating vectors are also carried out, in order to identify long-run structural relationships contained within the system. In practice this amounts to testing the null hypothesis that the first cointegrating vector (i.e. the first row of matrix β') takes some restricted form (reflecting the hypothesised structural relationship) against the alternative hypothesis of no restriction[39]. Normalising on FDI, the possible restricted forms of the first cointegrating vector were formulated as individual null hypotheses $H_1, H_2, \ldots, H_{11}$ and tested using the LR-test described in **Section 5.5**.

In each case the second cointegrating equation was left unrestricted, reflecting a structural relationship between EXP, IMP, GFCF and GDP based on national income accounting principles. Restricted forms of the second cointegrating vector were also tested, with the results shown in **Appendix E**. All restrictions were rejected at the 5% level of significance, suggesting that the second cointegrating vector should be left in its unrestricted form.

Table 6e: Testing restrictions on cointegrating matrix $\beta' = \begin{bmatrix} \beta_{1,FDI} & \beta_{1,EXP} & \beta_{1,GFCF} & \beta_{1,IMP} & \beta_{1,GDP} \\ \beta_{2,FDI} & \beta_{2,EXP} & \beta_{2,GFCF} & \beta_{2,IMP} & \beta_{2,GDP} \end{bmatrix}$

Null hypothesis	LR-stat	Probability
$H_1: \beta_1 = [1 \quad 0 \quad 0 \quad * \quad *]$	Chi-sq(1)=0.154	0.694
$H_2: \beta_1 = [1 \quad 0 \quad * \quad 0 \quad *]$	Chi-sq(1)=3.121	0.077*
$H_3: \beta_1 = [1 \quad 0 \quad * \quad * \quad 0]$	Chi-sq(1)=0.723	0.395
$H_4: \beta_1 = [1 \quad * \quad 0 \quad 0 \quad *]$	Chi-sq(1)=3.412	0.065*
$H_5: \beta_1 = [1 \quad * \quad 0 \quad * \quad 0]$	Chi-sq(1)=0.279	0.598
$H_6: \beta_1 = [1 \quad * \quad * \quad 0 \quad 0]$	Chi-sq(1)=3.063	0.080*
$H_7: \beta_1 = [1 \quad 0 \quad 0 \quad 0 \quad *]$	Chi-sq(2)=6.020	0.049**
$H_8: \beta_1 = [1 \quad 0 \quad 0 \quad * \quad 0]$	Chi-sq(2)=0.586	0.746
$H_9: \beta_1 = [1 \quad 0 \quad * \quad 0 \quad 0]$	Chi-sq(2)=5.559	0.062*
$H_{10}: \beta_1 = [1 \quad * \quad 0 \quad 0 \quad 0]$	Chi-sq(2)=11.593	0.003***
$H_{11}: \beta_1 = [1 \quad 0 \quad 0 \quad 0 \quad 0]$	Chi-sq(3)=20.764	0.000***

Note: the LR test statistic has an asymptotic Chi-square distribution under the null with degrees of freedom equal to the number of restrictions imposed. The first cointegrating equation is normalised on FDI, while the second cointegrating equation is normalised on exports. *, **, *** denote rejection at the 10%, 5% and 1% level respectively.

[39] It is arbitrary whether the restriction is placed on the first or the second cointegrating vector.

In **Table 6e**, All cases for which the IMP coefficient was restricted ($\beta_{1,IMP} = 0$) were rejected at the 10% level of significance. The hypotheses H_1, H_3, H_5 and H_8, which did not restrict the IMP coefficient, were not rejected. This is further evidence supporting the existence of a long-run equilibrium relationship between FDI and imports – consistent with Granger-causality testing which indicated a bi-directional relationship between FDI and IMP at the 5% level of significance.[40]

Of the hypotheses H_1, H_3, H_5 and H_8, H_8 is the most restrictive form – corresponding to a hypothesised long-run relationship between FDI and IMP, and excluding EXP, GFCF and GDP. Notably, H_8 is accepted with the highest probability (0.746). This implies that FDI may have a long-run structural relationship only with IMP, and not the other variables[41]. Again, this is consistent with the findings of the Granger-causality analysis which did not reveal any causal links running between FDI and EXP nor FDI and GFCF, and only very weak causality running from FDI to GDP.

6.6 VECM estimation output (restricted model)

A parsimonious VECM specification is obtained using the restriction identified above, and setting individual speed of adjustment coefficients with insignificant *t*-statistics (in the unrestricted model) equal to zero. An LR-test showed that the restrictions were jointly not rejected, with a probability of 0.800. The model estimates are shown in the table below. All *t*-statistics were significant at the 5% level and are given beneath the coefficient estimates where applicable. Adjusted R^2 statistics showed that the five equations explained between 38.4% and 61.4% of the variation in the corresponding variable.

[40] Cointegration between two or more time series indicates that there must be Granger-causality between them, though the converse is not true.
[41] A relationship cannot be completely ruled out, however, since the cointegrating vectors are not exactly orthogonal, and weak exogeneity was rejected.

Table 6f: Restricted Vector Error Correction estimates for FDI, EXP, GFCF, IMP and GDP						
Cointegrating coefficients – matrix β			Adjustment coefficients – matrix α			
Variable	CE1	CE2	Variable	CE1	CE2	Adj-R^2
FDI_{t-1}	1	0	ΔFDI	-0.732 [-3.964***]	0 (restricted)	0.614
EXP_{t-1}	0 (restricted)	1	ΔEXP	-0.010 [-3.107**]	0 (restricted)	0.384
$GFCF_{t-1}$	0 (restricted)	0.560 [11.657***]	ΔGFCF	0 (restricted)	-0.105 [-2.918***]	0.587
IMP_{t-1}	-0.232 [-12.041***]	-0.076 [-2.209**]	ΔIMP	-0.133 [-2.887***]	-0.269 [-2.853***]	0.415
GDP_{t-1}	0 (restricted)	-0.198 [-30.672***]	ΔGDP	0 (restricted)	0.440 [4.823***]	0.476

Note: the optimal number of lags was chosen as 4. Restrictions identified all cointegrating vectors. A likelihood ratio (LR) test was conducted on the binding restrictions and gave a Chi-square(6) statistic of 4.546 with probability 0.603, indicating that the restrictions were not able to be rejected and seemed to be valid. Normalisation was conducted on FDI and EXP in the cointegrating equations. The trend in the unrestricted model found to be insignificant and was removed in the restricted specification. **, *** denote significance at the 5% and 1% level respectively.

As can be seen from the restricted estimates, GDP and GFCF did not respond to deviations from long-run equilibrium in the first cointegrating vector, while FDI and EXP did not respond to the second cointegrating vector. Imports adjusted to previous period deviations in both cointegrating equations.

6.7 Model Diagnostics

To ensure that the model was not specified incorrectly it was subjected to a battery of diagnostic tests as outlined in **Section 5.6**. The full results of the tests are given in the appendices. Overall the diagnostic tests indicate that the model is reasonably well-specified.

6.7.1 Test for residual autocorrelation

Results of the LM-test show no evidence of residual autocorrelation in the model. The null hypotheses of no autocorrelation at lags 1 to h for $h = 1,2,\ldots,12$ are not rejected for both the Johansen (1995) LR-test and the Edgerton and Shukur (1999) *F*-test, at any meaningful level of significance.

6.7.2 Test for residual heteroskedasticity

Results of the White test show no evidence of residual heteroskedasticity in the model. The null hypothesis of no heteroskedasticity is not rejected at any meaningful level of significance.

6.7.3 Test for lag exclusion and stability

Results of the Wald lag exclusion tests show that lags 1 to 4 are jointly significant for all the variables in the model. Lags higher than 4 are jointly insignificant. This is good evidence that a lag length of 4 is optimal and has been correctly chosen.

6.7.4 Test for stability

Finally, examination of the roots of the AR characteristic polynomial showed that all roots (except the required three unit roots) lay within the unit circle and hence the model was stable.

6.8 Impulse Response Analysis

The parsimonious VECM specification obtained **Section 6.6** was then used to generate impulse response functions as described in **Section 5.7**. Orthogonalised impulses with magnitude equal to one standard deviation of the $\boldsymbol{\varepsilon}_t$ errors were generated using a Cholesky decomposition. The appropriate variable ordering was chosen on the basis of weak exogeneity tests carried out in **Section 6.4**. The ordering was EXP, FDI, GFCF, IMP, GDP (from most exogenous to least exogenous), although the impulse responses did not seem to be very sensitive to alternative orderings when these were examined. Impulse response functions are presented below – each graph traces the effect of a shock to one variable on the four other response variables.

Figure 6b: Impulse responses to a shock in FDI (Cholesky one S.D.)

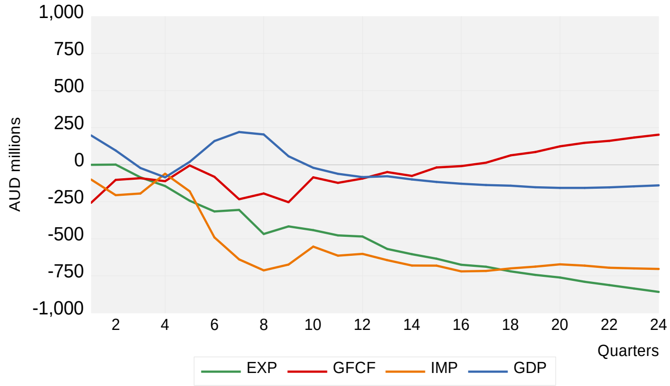


Figure 6c: Impulse responses to a shock in EXP (Cholesky one S.D.)

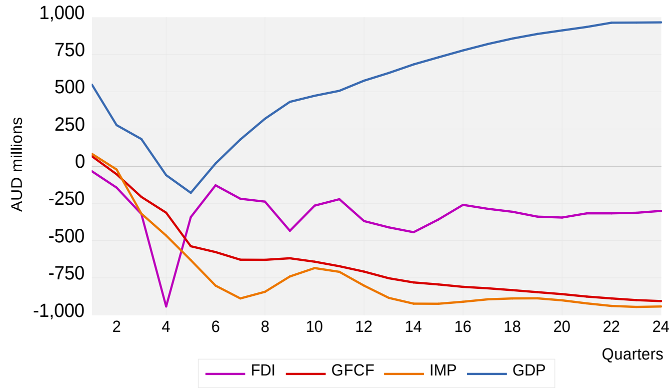


Figure 6d: Impulse responses to a shock in GFCF (Cholesky one S.D.)

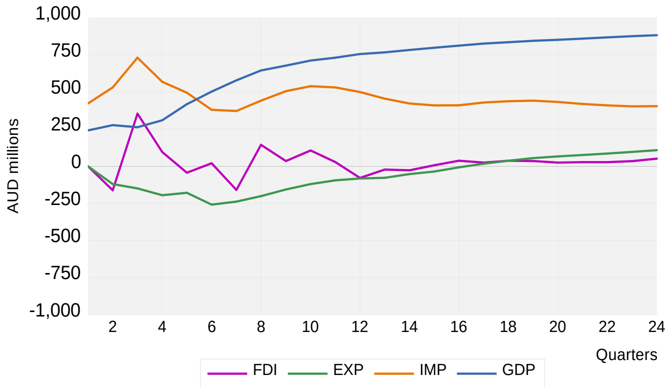


Figure 6e: Impulse responses to a shock in IMP (Cholesky one S.D.)

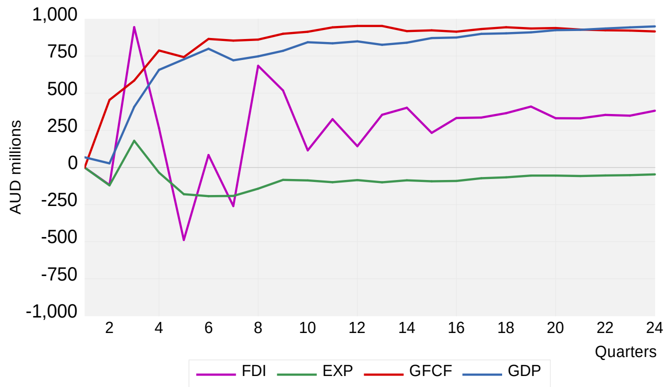
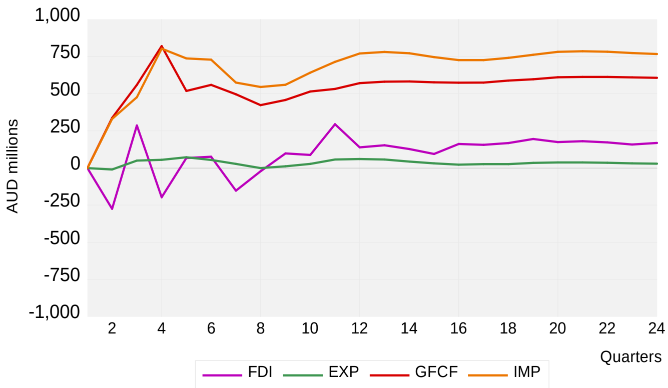


Figure 6f: Impulse responses to a shock in GDP (Cholesky one S.D.)



There are several notable features of the impulse responses which deserve to be pointed out. Most importantly for this analysis, **Figure 5b** shows the responses of EXP, GFCF, IMP and GDP to a one standard deviation shock in FDI. The response of GDP is initially positive but reverts back to zero after 4 quarters. From quarters 5 to 10 the response is once again positive but the long-run effect of FDI on GDP is slightly negative (though unlikely to be significantly different from zero). This supports the earlier hypothesis that there is no long-run relationship between FDI and GDP for the case of Australia.

The causal link running from FDI to imports was significant at the 5% level and a long-run cointegrating relationship was found between these two variables. **Figure 5b** shows that the effect of FDI on IMP is negative. FDI has a small immediate negative effect on imports which becomes strongly negative after the 4^{th} quarter. The negative response of imports stabilises at around -750 million AUD after the 8^{th} quarter. This is a very interesting result and suggests that FDI is import-substituting in Australia, with foreign firms' local production replacing final goods imports. This also indicates that foreign firms in Australia are not very intensive in their imports of intermediate goods, such that final goods imports decrease by more than intermediate imports increase.

The impact of FDI on exports is initially zero but becomes negative after the second quarter. The effect grows increasingly negative over the 24-quarter time horizon and the long-run effect is strongly negative. However, this effect may not be significant as no significant causal links were established between FDI and exports in the Granger-causality analysis in **Section 6.1**. This is a surprising result as foreign-owned firms in Australia are generally more export-oriented than local firms (ABS 2018). However as shown in **Figure 1f**, more than 60% of inward FDI flows to non-mining industries (such as finance, insurance, real estate, retail trade and others) where the link between FDI and exports is not immediately obvious. Thus, the government's claim that FDI drives exports could not be substantiated by this analysis.

The short-run effect of FDI on GFCF is negative but this turns positive after 15 quarters, with a slightly positive effect in the long-run (though again, this result was not significant in the Granger-causality analysis). Thus, there is no evidence to support FDI either directly crowding-in or crowding-out domestic investment.

Because FDI had a significant and negative effect on imports, and the relationship between imports and GFCF is significant and positive as shown in **Figure 5e**, this may indicate that FDI tends to decrease GFCF (and hence crowd-outs domestic investment) through its effect on imports. The two-step effect of FDI on GDP through imports is also negative, which further supports the hypothesis that FDI has a nil or even weakly negative effect on GDP in Australia.

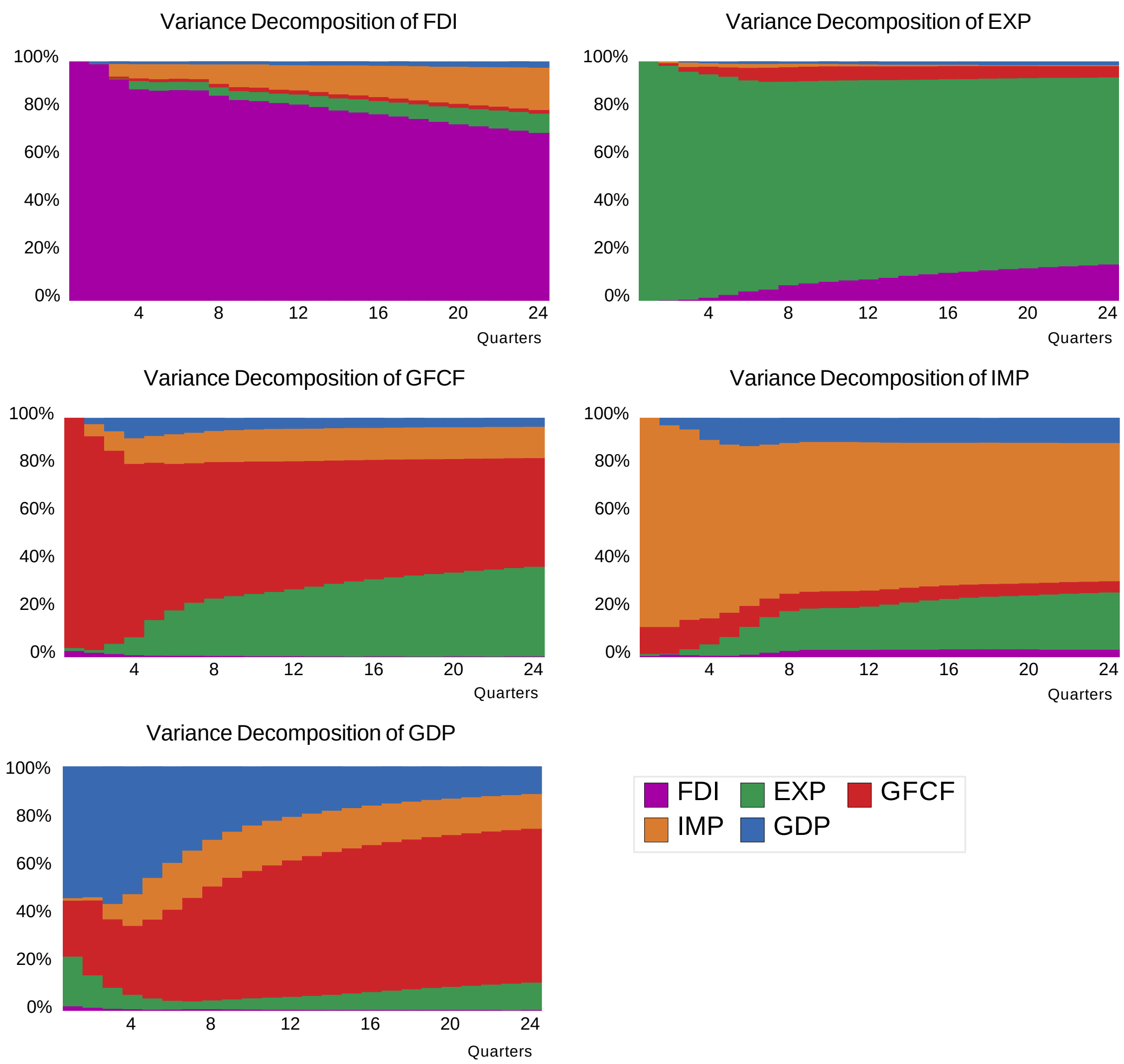
Imports were found to Granger-cause FDI at the 5% level, and **Figure 6e** shows imports have strongly positive effect on FDI after quarter 3. Although the effect becomes negative from quarters 4 to 7, a moderate positive effect is sustained after quarter 10. Thus, imports appears to have a positive effect on FDI in the long-run (which in turn reduces the level of imports).

To check that the model is specified correctly it is worth examining the other impulse response functions for those links which exhibited Granger-causality. As expected GDP had a positive effect on imports and GFCF in **Figure 6f**, and GFCF also had a positive effect on GDP in **Figure 6d**. Also as expected, exports had a positive immediate and long-run effect on GDP in **Figure 6c**. Other significant links that were found included that imports had a positive short-run and long-run effect on GFCF (**Figure 5e**) while exports tended to reduce both imports and GFCF (**Figure 6c**).

6.9 Forecast Error Variance Decomposition

In order to examine the proportion of each variable's movement attributable to shocks in the other variables, forecast error variance decompositions are computed over a time horizon of 24 quarters. These are calculated in the manner described in **Section 5.7** with the same Cholesky ordering as the impulse responses, namely EXP, FDI, GFCF, IMP, GDP. Once again, the ordering of the variables did not make much difference to the results.

Figure 6g: Forecast error variance decomposition of FDI, EXP, GFCF, IMP and GDP using Cholesky factors. Cholesky ordering: EXP, FDI, GFCF, IMP, GDP.



The top left panel supports the conclusion that variation in FDI is mainly explained by its own previous values, though imports do explain some of the variation at longer time horizons (approximately 20% after 24 quarters). This is consistent with the Granger-causality in **Section 6.3** and tests on the cointegration vector in **Section 6.5.**

FDI shocks explained almost none of the variation in GFCF and GDP, even in the long-run, as shown in middle left and bottom left panels. This supports the findings of earlier Granger-causality testing which revealed no causal links between FDI and GFCF and only very weak causality from FDI to GDP.

Variation in GCFC was mostly explained by shocks to itself, as well as exports (25-35%) and imports (10-15%) at longer-time horizons. Most of the short-run variation in GDP was explained by shocks to itself, while its long-run variation was explained mostly by GFCF (approximately 40%), followed by imports, exports and itself.

Although FDI was shown to Granger-cause imports, FDI shocks only explained about 3% of the long-run variation in imports[42], implying that the effect of FDI on imports was small relative to the other variables and forces outside the model. Most of the long-run variation in imports is explained by shocks to itself (approximately 60%) exports (approximately 20%) and GDP (approximately 10%). This also indicates that the effect of imports on FDI is stronger than the effect of FDI on imports.

6.10 Further Discussions and Extensions

There are several possible explanations for these findings that warrant further investigation. First, it is possible that a sizeable portion of Australian inward FDI does not finance fixed capital formation. This may seem counter-intuitive, but since FDI is simply a balance of payments measure, it does not necessarily reflect actual spending by foreign firms in acquiring fixed capital, and hence is not "investment" in the true economic sense. Rather, FDI is an accounting measure of financial flows, and may instead be symptomatic of non-productive asset transfers.

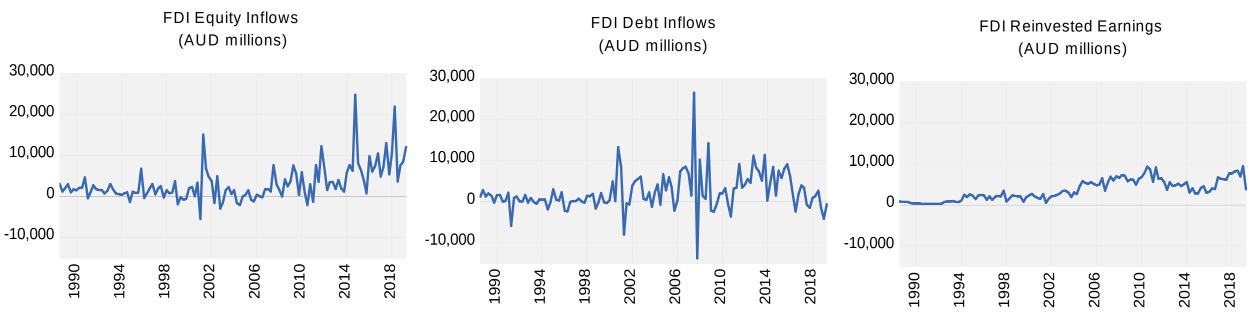
According to the 6th Balance of Payments Manual (IMF 2013) and OECD Benchmark Definition of FDI (OECD 2008) which together set the international standards for FDI accounting, FDI equity flows include common and preferred shares in subsidiaries and associates, capital contributions and disinvestments, changes in reserves, dividends, branch earnings and reinvested earnings. FDI debt includes intercompany loans, deposits, trade credit and any marketable debt securities (see **Figure 1e**). The extent to which these financial flows represent "investment" in the economic sense (i.e. expenditure on capital goods) is not clear.

[42] The existence of Granger-causality does not offer any insight into the magnitudes of causal effects, so this result is not necessarily a surprise.

FDI flows may also reflect the activity of funds of funds, funds in transit (e.g. via special purpose vehicles) and reclassifications of portfolio to direct investment (e.g. if an investor owning a 9% stake in an Australian company increases their ownership to 11%). These FDI flows are unlikely to have substantive effects on the economy.

It is worth investigating whether FDI equity, reinvested earnings and FDI debt do indeed have different macroeconomic effects. Quarterly data published by the ABS is seasonally-adjusted and deflated for each of these "components" of FDI, with time plots given below for data over the period Q3/1988 to Q2/2019.[43]

Figure 6h: Time plots of real FDI equity inflows, real FDI debt inflows and real FDI reinvested earnings over the period September 1988 to June 2019



Applying the Toda-Yamamoto procedure once again, three over-fitted VAR$(k + d_{\max})$ models are estimated for FDI, EXP, GFCF, IMP and GDP as per **Section 6.3**, replacing FDI with FDI equity, FDI debt and FDI reinvested earnings in each case. For all three models the maximum order of integration in the system is one, and $k = 5$. Granger-causality tests were conducted using the modified Wald test as usual, with results presented in **Table 6g**.

[43] The ABS only began compiling statistics on FDI by components in Q3/1988.

Table 6g: Pairwise Granger-causality tests on FDI split by components, using the Toda-Yamamoto modified Wald test				
Null hypothesis			MWald Stat.	Probability
EXP	does not Granger cause	FDI Equity	7.889	0.162
GFCF	does not Granger cause	FDI Equity	7.848	0.165
IMP	does not Granger cause	FDI Equity	7.978	0.157
GDP	does not Granger cause	FDI Equity	3.083	0.687
FDI Equity	does not Granger cause	EXP	3.737	0.588
FDI Equity	does not Granger cause	GFCF	4.555	0.473
FDI Equity	does not Granger cause	IMP	11.519	0.042**
FDI Equity	does not Granger cause	GDP	7.683	0.175
EXP	does not Granger cause	FDI Debt	4.405	0.493
GFCF	does not Granger cause	FDI Debt	2.722	0.743
IMP	does not Granger cause	FDI Debt	14.374	0.013**
GDP	does not Granger cause	FDI Debt	1.734	0.885
FDI Debt	does not Granger cause	EXP	1.423	0.922
FDI Debt	does not Granger cause	GFCF	4.367	0.498
FDI Debt	does not Granger cause	IMP	7.601	0.180
FDI Debt	does not Granger cause	GDP	7.523	0.185
EXP	does not Granger cause	FDI Reinv.	5.338	0.376
GFCF	does not Granger cause	FDI Reinv.	6.974	0.223
IMP	does not Granger cause	FDI Reinv.	4.759	0.446
GDP	does not Granger cause	FDI Reinv.	4.810	0.440
FDI Reinv.	does not Granger cause	EXP	8.344	0.138
FDI Reinv.	does not Granger cause	GFCF	1.399	0.924
FDI Reinv.	does not Granger cause	IMP	1.718	0.887
FDI Reinv.	does not Granger cause	GDP	6.953	0.224

Note: FDI Reinv. refers to the reinvested earnings component of FDI. FDI Equity refers exclusively to equity transactions and does not include reinvested earnings. The lag order k was chosen to be 5 on the basis of the Akaike Information Criterion. This was also smallest lag order that ensured the residuals were free of autocorrelation. The lag order $d_{\max}$ was chosen as 1 since the maximum order of integration amongst the five series was 1. *, **, *** denote rejection at the 10%, 5% and 1% level respectively.

Contrary to expectations, there is hardly any difference between the three series in terms of causal links with the other variables[44]. It is interesting that the bi-directional causality between aggregate FDI and imports can be decomposed into uni-directional causality running from FDI equity to imports, and imports to FDI debt. However, the more stark result is the lack of Granger-causality between any of the FDI series and GFCF or GDP.

[44] It would be useful to conduct similar analysis for FDI inflows broken down by source country, and by industry (e.g. it is expected that mining-related FDI would behave quite differently to FDI in financial services), however, data with sufficient degrees of freedom is not available.

It is also possible that FDI into Australia does not generate positive spillovers through knowledge transfers, technical innovation, competition and inter-firm linkages, or that these effects are simply too weak to be detected at any meaningful level of significance. To investigate this theory further, the Toda-Yamamoto procedure is used to test whether there is any causality running between FDI and two common measures of productivity – real GDP per hour worked and real GDP per hour worked in the market sector. These series are generated from quarterly data on hours worked (total) and hours worked (market sector) published by the ABS.

Table 6h: Pairwise Granger-causality tests on FDI and measures of productivity, using the Toda-Yamamoto modified Wald test

Null hypothesis			MWald Stat.	Probability
FDI	does not Granger cause	Real GDP/Hours worked (in all sectors)	1.664	0.4351
FDI	does not Granger cause	Real GDP/Hours worked (in the market sector)	2.598	0.2728

Note: in each case the lag order k was chosen to be 2 on the basis of the Akaike Information Criterion. This was also smallest lag order that ensured the residuals were free of autocorrelation. The lag order $d_{\max}$ was chosen as 1 since the maximum order of integration amongst the series was 1 in each case.

In both cases the null hypothesis of no Granger-causality cannot be rejected, supporting the theory that inward FDI in Australia does not generate spillovers that improve productivity.[45] Thus, for the case of Australia, this analysis finds no evidence that inward FDI promotes economic growth via either the capital accumulation or the productivity-enhancing channel.

Finally, it is worth exploring the significant relationship between FDI and imports in more detail, since FDI was found to be import-substituting, and FDI equity Granger-caused imports at the 5% level of significance. The Toda-Yamamoto procedure was repeated on bivariate VARs between FDI equity and each of the various components of merchandise imports at the Standard International Trade Classification (SITC) at the 1-digit level. Imports data were quarterly spanning the period from Q3/1988 to Q2/2019, and were seasonally-adjusted and deflated by the implicit price deflator for imports. The results of the analysis are shown in **Table 6i.**

[45] This is consistent with the findings of both Boon (2011) and Kirchner (2012).

Table 6i: Pairwise Granger-causality tests on FDI on imports by SITC classification (1-digit level), using the Toda-Yamamoto modified Wald test				
Null hypothesis			MWald Stat.	Probability
FDI Equity	does not Granger cause	Food and live animals (0)	6.923	0.437
FDI Equity	does not Granger cause	Beverages and tobacco (1)	12.936	0.227
FDI Equity	does not Granger cause	Crude materials except fuels (2)	17.242	0.016**
FDI Equity	does not Granger cause	Mineral fuels and related (3)	0.019	0.891
FDI Equity	does not Granger cause	Animal and vegetable oils (4)	3.092	0.543
FDI Equity	does not Granger cause	Chemical and related products (5)	28.408	0.000***
FDI Equity	does not Granger cause	Manufactured goods (6)	25.130	0.002***
FDI Equity	does not Granger cause	Machinery and transport equip. (7)	7.699	0.565
FDI Equity	does not Granger cause	Miscellaneous manufactures (8)	8.313	0.403
FDI Equity	does not Granger cause	Other unclassified (9)	2.788	0.426

Note: in each case the lag order k was chosen the basis of the Akaike Information Criterion. The lag order $d_{\max}$ was chosen as 1 since the maximum order of integration amongst the series was 1 in each case.

These results demonstrate Granger-causality running from FDI equity to crude materials (except fuels) at the 5% critical level, and to chemical products and manufactured goods at the 1% critical level, supporting the finding of Nicholas et al. (2003) that FDI contributes to localising production of manufactured goods. Localised production also may be substituting for chemical and crude material imports. The dynamics of these relationships constitute an area for future research.

6.11 Summary of Results

Overall the results showed that there was a long-run relationship between FDI and imports with significant bi-directional causality. Impulse responses demonstrated that a shock to FDI induced a negative response in imports, suggesting FDI was import-substituting in Australia, while further causality testing suggested that this effect was localised to crude materials, chemical and manufacturing imports. No causal links or long-run relationships were detected between FDI and the other variables. Impulse response analysis showed that FDI had did not have the expected positive effect on GDP, while FEVD showed that the effects of FDI on the other variables was very weak. Additional Granger-causality tests showed that the equity, debt and reinvested earnings components of FDI had no effect on GDP, GFCF or exports when considered separately, and there was no evidence of causality between aggregate FDI and productivity.

7 Conclusion

This thesis set out to investigate the effects of inward foreign direct investment on economic growth, fixed capital formation, exports and imports for the case of Australia. This was an important question given that FDI is usually considered to be beneficial to the Australian economy, set against the narrative that foreign investment bridges the shortfall between national savings and investment and thereby raises standards of living. Indeed, policymakers up to the ministerial level assert that FDI promotes economic growth in Australia through capital accumulation, knowledge and technological spillovers, enhanced global supply chain linkages and increased exports. This is despite the lack of comprehensive empirical research on the effects of FDI in the Australian context.

Although the theoretical literature does lend support to the government's position on the whole, the effects of FDI are largely dependent on idiosyncratic characteristics of particular economies and the nature of the FDI itself. The question has thus become an empirical one – though the empirical literature is also far from conclusive, pointing to highly heterogeneous dynamics across countries.

For the case of Australia, a time series analysis was chosen in order to reveal dynamic inter-linkages, as there was assumed to be endogeneity amongst the variables under investigation. A VAR/VECM framework, combined with the Toda-Yamamoto procedure for Granger-causality testing, was adopted after careful consideration of the pros and cons of various approaches used in the empirical literature. The method was developed in consideration of all possibilities with respect to integration and cointegration of the data, and the final VECM subjected to rigorous diagnostic testing to ensure the model was correctly specified.

The results indicated that there was no causality running from FDI to GFCF or exports, and only very weak causality running from FDI to GDP. However, there was evidence for bi-directional causality between FDI and imports. Cointegration analysis supported the hypothesis of a long-run equilibrating relationship between FDI and imports, and the hypothesis that FDI had no long-run relationship with GDP, GFCF and exports could not be rejected. Impulse response analysis of the restricted-form VECM indicated that FDI had a negative relationship with imports after four quarters and in the long-run. FDI also had a slightly negative long-run relationship with GDP both directly and indirectly (through imports), and a negative indirect effect on GFCF. FEVD analysis supported the conclusion that FDI had little to no effect on any of the other variables. Further Granger-causality analysis detected no causal linkages between any of the individual components of FDI (equity, reinvested earnings and debt) and the other variables under investigation. There was also no causal link between FDI and productivity in the case of Australia.

This is a surprising result which runs counter to the government's narrative. The most likely explanation is that FDI is not investment in the economic sense of the term and does not reflect capital investment by foreign firms. Indeed, it should not be thought of this way. Instead, FDI represents investment in the finance sense of the term and is merely a balance of payments concoction, reflecting many types of transactions and asset transfers which have no material effect on the macroeconomy. Therefore, politicians and policymakers ought to look for other measures of the actual contribution of foreign firms to the Australian economy and cease the relentless pursuit of FDI for FDI's sake. More detailed consideration of the effects of sector-specific inward FDI, as well as the bi-directional relationship between FDI and imports, would be promising areas of future research.

Appendices

A. Abbreviations

Table A1: Abbreviations used throughout this thesis	
ABS	Australian Bureau of Statistics
ADF	Augmented Dickey-Fuller
AR	Autoregressive
ARDL	Autoregressive Distributed Lag
ASEAN	Association of Southeast Asian Nations
CE	Cointegrating Equation
CGE	Computable General Equilibrium (model)
ECT	Error Correction Term
FDI	Foreign Direct Investment
FEVD	Forecast Error Variance Decomposition
FIRB	Foreign Investment Review Board (Australia)
GDP	Gross Domestic Product
GNI	Gross National Income
GFCF	Gross Fixed Capital Formation
KPSS	Kwiatkowski-Phillips-Schmidt-Shin
LM	Lagrange Multiplier
LR	Likelihood Ratio
MNE	Multinational Enterprise
MWald	Modified Wald (test, or test statistic)
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary Least Squares (regression, estimation)
SAARC	South Asian Association for Regional Cooperation
SITC	Standard International Trade Classification
SEASABS	SEASonal analysis, ABS standards
SVECM	Structural Vector Error Correction Model
TFP	Total Factor Productivity
UNCTAD	United Nations Conference on Trade and Development
VAR	Vector Autoregression
VECM	Vector Error Correction Model
VMA	Vector Moving Average
ARIMA	Autoregressive Integrated Moving Average

B. Data sources

Table A2: Data sources used in this thesis	
Source	Data
ABS Catalogue 5302.0 – Balance of Payments and International Investment Position, June 2019	Australia inward FDI flows; FDI equity, debt and reinvested earnings flows; portfolio, derivative and other inward investment stocks and flows
ABS Catalogue 5206.0 – Australian National Accounts: National Income, Expenditure and Product, June 2019	Australia GDP; GFCF; imports; exports; implicit price deflators for components of GDP (including GFCF)
ABS Catalogue 5352.0 – International Investment Position, Australia: Supplementary Statistics, 2018	Australia inward FDI stock by country and country groups; FDI stock by industry classification
ABS Catalogue 5368.0 – International Trade in Goods and Services, Australia, August 2019	Australia imports by SITC classification (monthly)
UNCTADStat Data Center – Foreign Direct Investment	Global annual FDI stocks and flows (measured in USD current prices); global FDI stocks/GDP ratios; global FDI flows/GFCF ratios

C. VECM unrestricted output

Table A3: Unrestricted Vector Error Correction estimates for FDI, EXP, GFCF, IMP and GDP									
Cointegrating equation coefficients – matrix β					Speed of adjustment coefficients – matrix α				
Variable	CE1	t-stat	CE2	t-stat	Variable	CE1	t-stat	CE2	t-stat
FDI_{t-1}	1	N/A	0	N/A	ΔFDI	-0.841	-4.118	0.487	1.298
EXP_{t-1}	0	N/A	1	N/A	ΔEXP	-0.112	-2.132	-0.046	-0.476
$GFCF_{t-1}$	0.004	0.034	0.565	12.058	ΔGFCF	0.006	0.088	-0.150	-2.223
IMP_{t-1}	-0.289	-1.745	-0.081	-1.198	ΔIMP	-0.119	-2.229	-0.282	-2.871
GDP_{t-1}	-0.010	-0.125	-0.394	-12.319	ΔGDP	-0.078	-1.306	0.420	3.853
Trend	75.059	0.576	-13.697	-0.258					

The optimal number of lags was chosen as 4. The trend specification for VECM estimation was the same as in the Johansen procedure, i.e. allowing for a linear deterministic trend in both the levels data and cointegrating equation. The cointegrating vectors were normalised on FDI and EXP.

D. Weak exogeneity test results

Table A4: Test for weak exogeneity of FDI, EXP, GFCF, IMP and GDP		
Null hypothesis	LR-stat	Probability
FDI is weakly exogenous to the system	9.528	0.009
EXP is weakly exogenous to the system	4.691	0.096
GFCF is weakly exogenous to the system	12.297	0.002
IMP is weakly exogenous to the system	14.402	0.001
GDP is weakly exogenous to the system	18.507	0.000

Note: The LR test statistic has an asymptotic Chi-square distribution with 2 degrees of freedom under the null. For each variable, both coefficients of the loading matrix α corresponding to that variable were tested to see whether they were jointly different from zero.

E. Hypothesis tests on the second cointegrating vector

Table A5: Testing restrictions on cointegrating matrix $\beta' = \begin{bmatrix} \beta_{1,FDI} & \beta_{1,EXP} & \beta_{1,GFCF} & \beta_{1,IMP} & \beta_{1,GDP} \\ \beta_{2,FDI} & \beta_{2,EXP} & \beta_{2,GFCF} & \beta_{2,IMP} & \beta_{2,GDP} \end{bmatrix}$		
Null hypothesis	**LR-stat**	**Probability**
$H_1: \beta_2 = [0 \quad 1 \quad 0 \quad * \quad *]$	Chi-sq(1) = 16.390	0.000***
$H_2: \beta_2 = [0 \quad 1 \quad * \quad 0 \quad *]$	Chi-sq(1) = 5.231	0.022**
$H_3: \beta_2 = [0 \quad 1 \quad * \quad * \quad 0]$	Chi-sq(1) = 19.814	0.000***
$H_4: \beta_2 = [0 \quad 0 \quad 1 \quad * \quad *]$	Chi-sq(1) = 35.173	0.000***
$H_5: \beta_2 = [0 \quad 1 \quad 0 \quad 0 \quad *]$	Chi-sq(2) = 33.075	0.000***
$H_6: \beta_2 = [0 \quad 1 \quad 0 \quad * \quad 0]$	Chi-sq(2) = 33.288	0.000***
$H_7: \beta_2 = [0 \quad 1 \quad * \quad 0 \quad 0]$	Chi-sq(2) = 34.311	0.000***
$H_8: \beta_2 = [0 \quad 0 \quad 1 \quad * \quad 0]$	Chi-sq(2) = 37.283	0.000***
$H_9: \beta_2 = [0 \quad 0 \quad 1 \quad 0 \quad *]$	Chi-sq(2) = 35.899	0.000***
$H_{10}: \beta_2 = [0 \quad 0 \quad 0 \quad 1 \quad *]$	Chi-sq(2) = 35.375	0.000***

Note: the LR test statistic has an asymptotic chi-square distribution under the null with degrees of freedom equal to the number of restrictions imposed. The first cointegrating equation is normalised on FDI. **, *** denote rejection at the 10%, 5% and 1% level respectively.

F. LM autocorrelation test

Table A6: Restricted VECM residual autocorrelation LM test results				
Lag	LR-stat	Probability	Edgerton F-stat	Probability
1	21.970	0.638	0.877	0.638
2	43.629	0.725	0.867	0.727
3	59.207	0.910	0.776	0.911
4	88.832	0.780	0.876	0.788
5	124.512	0.496	0.991	0.515
6	146.243	0.572	0.962	0.603
7	188.701	0.227	1.082	0.270
8	216.001	0.208	1.079	0.270
9	230.668	0.384	1.002	0.491
10	254.180	0.415	0.980	0.565
11	297.911	0.164	1.056	0.331
12	315.891	0.253	0.995	0.517

Note: the null hypothesis is no serial correlation at lags 1 to h.

G. Lag exclusion tests

Table A7: VECM lag exclusion Wald coefficient restriction tests

Lag	Probability					
	ΔFDI	ΔEXP	ΔGFCF	ΔIMP	ΔGDP	Joint Test
1	0.583	0.085*	0.004***	0.000***	0.000***	0.000***
2	0.272	0.109	0.605	0.012**	0.000***	0.000***
3	0.388	0.727	0.643	0.005***	0.000***	0.000***
4	0.079*	0.359	0.024	0.021**	0.006***	0.000***
5	0.385	0.653	0.816	0.491	0.504	0.854
6	0.539	0.246	0.251	0.514	0.342	0.412
7	0.411	0.114	0.949	0.731	0.450	0.714

Note: the null hypotheses are i) that lag coefficients are individually equal to zero, and ii) jointly equal to zero for all variables at that lag length. The test statistic has chi-square distribution with 5 degrees of freedom under the null hypothesis in i); and 25 degrees of freedom under the null hypothesis in ii). *, **, *** denote rejection at the 10%, 5% and 1% level respectively.

H. Heteroskedasticity white test

Table A8: White residual heteroskedasticity test (no cross terms)

	Chi-sq	Degrees of Freedom	Probability
Joint test	672.746	660	0.357

Note: the null hypothesis is no residual heteroskedasticity.

I. Roots of the AR polynomial

Table A9: Restricted VECM – Characteristic roots of the AR Polynomial

Number	Root	Modulus	Number	Root	Modulus
1	1.000	1.000	12	-0.691 – 0.333i	0.768
2	1.000	1.000	13	-0.691 + 0.333i	0.768
3	1.000	1.000	14	-0.708 – 0.057i	0.710
4	0.931	0.931	15	-0.708 + 0.057i	0.710
5	0.619 – 0.591i	0.856	16	0.681 + 0.153i	0.698
6	0.619 + 0.591i	0.856	17	0.681 – 0.153i	0.698
7	-0.596 + 0.577i	0.830	18	-0.358 – 0.576i	0.678
8	-0.596 – 0.577i	0.830	19	-0.358 + 0.576i	0.678
9	0.812	0.812	20	-0.195 – 0.646i	0.675
10	0.264 + 0.763i	0.808	21	-0.195 + 0.646i	0.675
11	0.264 - 0.763i	0.808	22	0.334 + 0.523i	0.621

Note: the model specification imposes 3 units roots. This is equal to the number of variables (5) minus the number of cointegrating vectors (2).

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