Detection and Analysis of the Causal Relation between Tourism and Greenhouse Gas Emission: An Empirical Approach

by

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Declaration of Authorship

I, Akanda Wahid -Ul- Ashraf, declare that this thesis titled, 'Detection and Analysis of the Causal Relation between Tourism and Greenhouse Gas Emission: An Empirical Approach' and the work presented in it are my own. I confirm that:

- This work was done wholly while in candidature for a research degree at this University.
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
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Abstract

Faculty of Science and Technology

Masters by Research(MRes)

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Manmade climate change is a threat to the inhabitants of our planet and greenhouse gas emissions have been identified as the main cause of this climate change. In order to reduce the effects of climate change, we need to significantly reduce emissions of greenhouse gasses to the atmosphere. While the tourism industry clearly contributes to greater emissions from aviation, but other sectors of emissions besides aviation are also influenced by tourism activities. In order to reduce the overall emissions significantly it is necessary to also identify the wider range of tourists impacts across all economic sectors which are contributing to greenhouse gasses emissions. The overall carbon footprint for a given country is estimated by calculating emissions from all different economic sectors such as agriculture, transportation etc. There has been a lack of research which empirically identifies how tourists activities manifest as carbon emissions across the full range of economic sectors, not just aviation. This study develops a method to identify causal relations between tourists numbers and greenhouse gas emissions across a range of economic sectors using data for the United Kingdom, Australia and 20 European Union countries. To perform time series causality analysis a combination of the established Granger causality test, and the novel Convergent Cross mapping (CCM) has been used. Convergent Cross mapping (CCM) has not previously been used for this application in tourism research and it overcomes some of the limitations associated with Granger causality analysis for the data available. The causality analysis performed revealed several causal links among different sectors of emissions with tourist numbers. It shows that in the UK, inbound tourist numbers are causing an increase in emissions from the category of Waste Management and also there is some evidence that increased emissions from Business sectors are caused by Tourist numbers. In Australia there is weak evidence that Tourist numbers might be causing increased emissions from the sectors of Industrial Processes and Product Use. This identification of a causal relationship between tourists numbers and wider economic sectors emissions contributes significantly to our understanding of the overall impact of tourism on greenhouse gas emissions in each case. In addition to this, in the UK and Australia, emissions from Agriculture seems to be causing Tourist numbers. These reverse causal effects are argued as due to the effects of economic third-variables, which might be influencing both emissions and tourism.

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Abbreviations

GHG	Greenhouse Gas
CCM	Convergent Cross Mapping
EU	European Union
LULUCF	Land use, land-use change and forestry
VEC	Vector Error Correction
VECM	Vector Error Correction Model
VAR	Vector Autoregression
AR	Autoregression
ADF	Augmented DickeyFuller
IPCC	Intergovernmental Panel on Climate Change
WTTC	World Travel & Tourism Council
DECC	The Department of Energy & Climate Change
AIC	Akaike Information Criterion
SC	Schwarz Criterion
HQ	HannanQuinn Information Criterion
PM	Portmanteau Test
LM	BreuschGodfrey serial correlation Lagrange Multiplier test
OLS	Ordinary Least Square
MSW	Municipal Solid Waste

Chapter 1

Introduction

Climate change due to anthropogenic greenhouse gas emissions is threatening our planet and its inhabitants. To save this planet from the catastrophic effects of climate change, a significant reduction in greenhouse gas emissions is necessary. It is an urgent need for the survival of humankind and every other living creature that necessary steps are taken which will effectively reduce the amount of greenhouse gases (GHG) emissions to the atmosphere and this necessitates identification of the major carbon emissions sources across different sectors (Pirani and Arafat, 2014).

Tourism is a major contributor to the modern economy. In fact for some countries the main economic driving force is tourism. Tourism is creating new job opportunities [1] and the locals directly feel the pace of economic development as tourist arrival increases. According to the World Travel & Tourism Council (2015), travel and tourism have massive contributions to GDP, up to 10% of the global GDP which is US$7.6 trillion. Contributions to the world's GDP from travel and tourism has been estimated to increase by 3.7% for the year of 2015 (World Travel & Tourism Council, 2015). Due its huge importance in the modern economy and ever-growing demand, it is vital to transform the current tourism industry into a more sustainable tourism industry. Tourism has adverse affects on a country's environment, culture, law and order situation etc and among them environmental impact is considered to be the most important (Scott et al., 2008). It is already known that tourism is associated with greenhouse gas emissions, mainly due to the huge dependency on air travel of the tourists in order to move long distances (Scott et al., 2008). Besides aviation there are other economic sectors of emissions categorised by the Intergovernmental Panel on Climate Change (IPCC). However, the effects of tourism on these sectors is not clear. There exists a substantial research gap to identify the environmental impact of tourists across different sectors of emissions besides aviation

[1] 1 in 11 jobs globally according to World Travel & Tourism Council (2015)

and this wider understanding is vital if we are to fully understand tourists impacts. A tourism carbon footprint analysis could provide a good theoretical insight on how tourists are influencing different emission sources as Dwyer et al. (2010) have shown. However to build a more precise carbon footprint model it would be better to identify which sectors of emissions are needed to be included based on empirical evidence. It is also important to identify the indirect influences(e.g. tourism demand for increasing electricity might result in more burning of fossil fuel which leads to more emissions (Page and Connell, 2008, p.42)). At the same time, the effect of tourists on GHG emissions may vary from country to country. This is mainly due to the diversity in variables such as a country's economy, geographical location, culture, transportation facility etc.

To identify the environmental impact of tourists across different sectors of emissions four statistical methods are being used in this research. These methods are:

1. Vector Auto Regression (VAR) Model Granger Non-causality Test (Granger)
2. Vector Error Correction (VEC) Model Granger Non-causality Test (Granger)
3. Convergent Cross mapping (CCM)
4. Multispatial CCM (CCM)

Among these four methods the first two are classified as a Granger casualty test which is a very widely used econometric tool, while the last two methods are based on CCM, which and is a comparatively new but promising statistical causality analysis method based on the theory of deterministic nonlinear dynamical systems. In this study, primarily, the United Kingdom and Australia have been used as case studies for identifying tourism influenced GHG emission sectors. The choice of these two countries is due to the following reasons:

- both are big island tourist destinations, which makes it more reliable and easier to estimate inbound tourist numbers.
- availability and accessibility of tourist and greenhouse gas data
- these two countries have completely different types of climate which allow highlighting differences to be highlighted in terms of tourists impact on emissions.

Also, tourism and emissions from 20 other EU countries have been used. Lee and Brahmasrene (2013) has already applied Granger causality on those countries with similar sets of emissions and tourism data sets and concluded no causal relation between carbon emission and tourism. This is mainly to test if CCM based approach could identify causality whereas Granger causality has failed to do so.

1.1 Aims and Objectives

Aims and objectives of this research are as follows:

1. Identify causal links between tourism and greenhouse gases using time series data of inbound tourist number and different sectors of emissions in the UK and Australia. Two statistical causal detection methods are being used i) Granger causality and ii) Convergent Cross Mapping (CCM).

2. From academic literature, identify and discuss the scope and limitations associated with these two causal detection methods, Granger causality and CCM.

3. Compare two different causality detection methods, Vector Autoregression and Vector Error correction models based Granger causality, and Convergent Cross Mapping (CCM).

4. Apply multispatial CCM for existing data from 20 EU countries in order to test for causality between tourism and greenhouse gas emissions across different economic sectors.

Chapter 2

Literature Review

2.1 Importance of Tourism

Tourism is a major contributory factors to the economy, an analysis of 27 European countries revealed that tourism directly results in economic growth and more precisely 1% of tourism receipts are responsible for 0.498% of economic growth[1](Lee and Brahmasrene, 2013). The evidence which links economic growth with tourism dates back to as early as 1976 where a case study for Hawaii showed that income is significantly influenced by the tourism industry (Ghali, 1976). To prove or investigate links between tourism and economic growth, statistical causality analysis is used.In order to find links between tourism and economic variables, the Granger causality approach is the most commonly method. Tourism-economic growth Granger causality analysis has started to emerge at a high pace since Balaguer and Cantavella-Jorda (2002) first applied the Granger causality test to investigate causal relations between tourism and economic growth. After that, there have been numerous research papers published where Granger causality has been used to prove causal relations between tourism and economic growth. In a literature survey, Pablo-Romero and Molina (2013) listed as many as 63 studies aimed at identifying causal relations between tourism and economic growth and 41 of them supports the idea of tourism causing economic growth. However, 12 of those studies also found bidirectional causal relations, which is the inverse causality from economic variables to touristic variables besides tourism causing economic growth. These bidirectional causalities are interpreted as economic growth itself having an influence on tourism numbers as well as tourism having a positive impact on the economy.

[1]Economic growth measured as positive percentage change in GDP

2.2 Tourism and Greenhouse Gas Emission

It is well known to the tourism and environmental scientists that tourist activities are associated with greater carbon emissions (Scott et al., 2008). However, the reason behind linking carbon emissions with tourism is mainly because of the associated air travel. Due to tourism's huge dependency on air transportation, it is estimated that tourism contributes around 5% of the global carbon emissions (Scott et al., 2008). As this study investigates, besides aviation, there are also other sectors of emissions-influenced by tourists (Dwyer et al., 2010). In a tourism carbon footprint analysis for Australia,the GHG emissions by tourism have been divided into two main categories, direct and indirect emissions (Dwyer et al., 2010). The direct carbon emission associated with tourism are considered as follows: (Dwyer et al., 2010, p.362):

- accommodation
- domestic air transport
- food and drink
- non-air transport
- shopping
- all other industries

While the indirect sectors are broader in categories (Dwyer et al., 2010, p.364) and they are mainly:

- agriculture
- gas
- chemical products
- petrol refinery
- electricity produced by gas iron steel
- air transport
- business services
- trade
- forestry and fishery

2.3 Greenhouse Gases

Greenhouse gasses are a number of gasses which are responsible for Climate Change. The Intergovernmental Panel on Climate Change(IPCC)'s Guidelines for National Greenhouse Gas Inventories included the following greenhouse gasses for the inventory report (Chapter 2 Eggleston H.S., 2006, p.5):

- carbon dioxide (CO_2)
- methane (CH_4)
- nitrous oxide (N_2O)
- hydrofluorocarbons(HFCs)
- perfluorocarbons(PFCs)
- sulphur hexafluoride (SF_6)
- nitrogen trifluoride (NF_3)
- trifluoromethyl sulphur pentafluoride(SF_5CF_3)
- halogenated others ($C_4F_9OC_2H_5$, $CHF_2OCF_2OC_2F_4OCHF_2$, $CHF_2OCF_2OCHF_2$)
- and other halocarbons not covered by the Montreal Protocol including CF_3I, $CH_2Br_2CHCl_3$, CH_3Cl,CH_2Cl_2

Besides all the above-mentioned gases the IPCC's guidelines also provide information to report gases named as, "other gases" and those are: nitrogen oxides (NO_x), ammonia (NH_3), non-methane volatile organic compounds (NMVOC), carbon monoxide (CO) and sulphur dioxide (SO_2).

By following the IPCC's guideline UK and Australia have divided their greenhouse gasses into the following categories (Department of the Environment, 2014, p.37), (Department of Energy & Climate Change(DECC), 2014, p.8):

Name of Gasses
Carbon dioxide
Methane
Nitrous oxide
Specified hydrofluorocarbons
Specified perfluorocarbons
Sulphur hexafluoride

Table 2.1: Different greenhouse gasses considered for UK and Australia

GHGs are measured by combining emissions from different sources consisting of many divisions and subdivisions. The main division of different sources which are considered as different sectors of emissions for in study are as follows (Eggleston H.S., 2006, Chapter 2):

- Energy
- Industrial Processes and Product Use (IPPU)
- Agriculture, Forestry and Other Land Use (AFOLU)
- Waste
- other (e.g., indirect emissions from nitrogen deposition from non-agriculture sources)

Each of these categories are subdivided into more categories, for example, transportation is subdivided into emissions from car and others but here, in this research, only the main sectors or categories are considered. The sum of emissions and removals from all categories and sub-categories is considered to be the total national emission. However, one exception is, emission from fuel used in ships and aircraft engaged in international transport is not considered in this national total and they are reported separately and not considered in this analysis (Chapter 2 Eggleston H.S., 2006, p.5). The next page contains more detailed information with multiple subcategories.

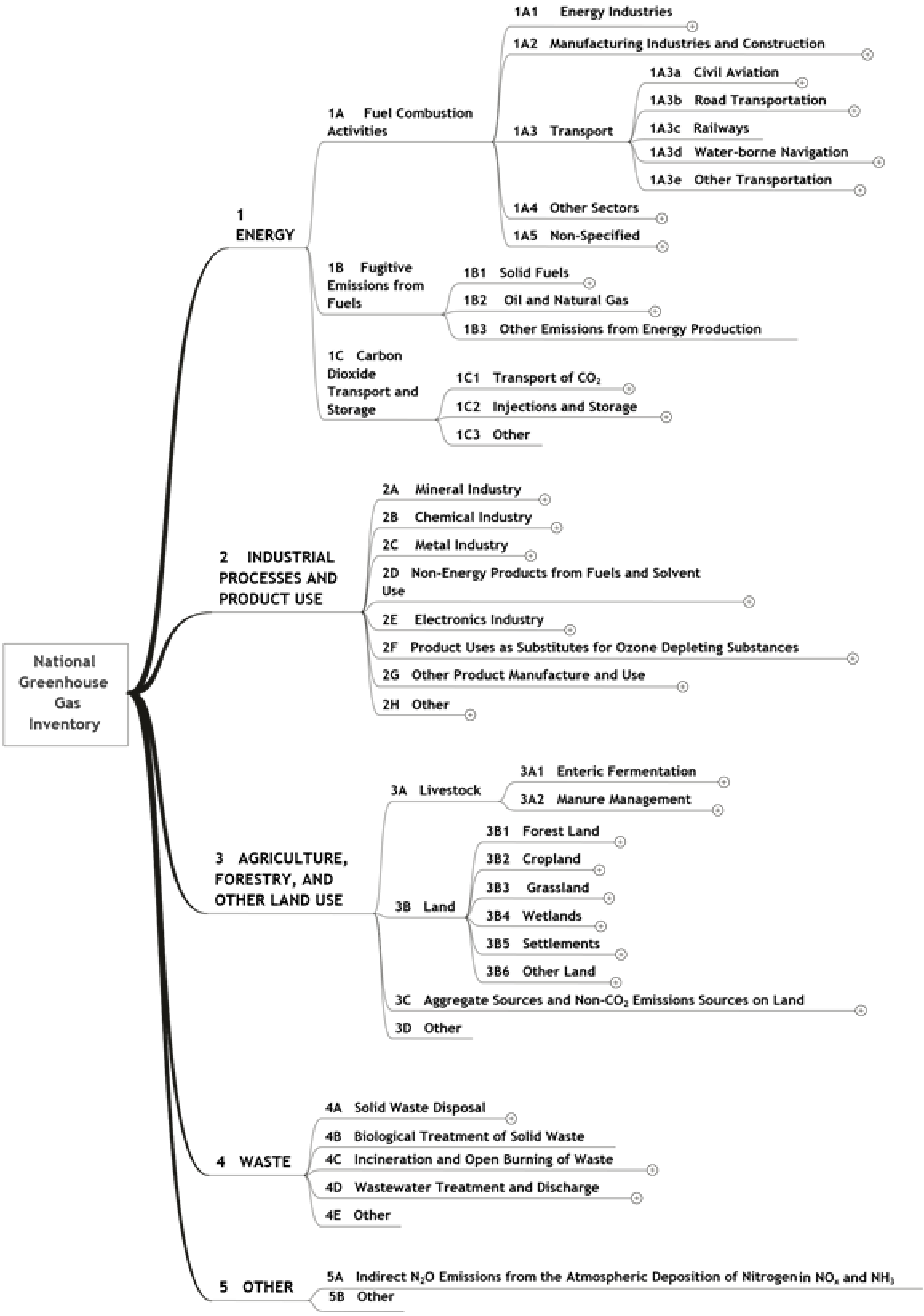

FIGURE 2.1: Different Categories of Emission (p.6 Eggleston H.S., 2006, Figure 1)

Data for UK and Australia has been collected from each of these country's governmental website. According to the IPCC's guideline in the figure 2.1 the Australian emission data are divided into multiple sectors as shown in appendixA (Department of the Environment, 2014, p.46). The UK's Department of Energy & Climate Change(DECC) (2014) categorised their emissions according to the following sectors:

National Communications sector	Main activities included in the sector
Energy supply from power stations	Power stations, refineries, manufactured solid fuels
Transport	Road transport, domestic aviation, railways
Business	Industrial combustion, refrigeration, air conditioning
Residential	Combustion, aerosol and non-aerosol products
Agriculture	Enteric fermentation, manure management,miscellaneous combustion
Waste management	Waste disposal, waste incineration
Industrial process	Production of mineral products, chemical industry
Public	Combustion from health, education and government buildings
LULUCF	Converting land to cropland (and vice versa)

Table 2.2: UK different sectors of emission

2.4 GHG Emission and Climate Change

In the Synthesis Report(SYR) of three intergovernmental Panels on Climate Change, the Fifth Assessment Report (AR5), it is stated that emissions are mainly caused by economic and population growth, and its anthropogenic (caused by human activity) and it is extremely likely[2] that GHG have been the dominant cause of the global warming which has been observed since mid-20th century (Pachauri et al., 2014).

High carbon and other GHG emissions are linked with rising global temperatures. The relation between carbon emissions and temperature is believed to be complex and there are several feedback loops in action from both directions (van Nes et al., 2015). For instance, higher CO_2 causes higher global temperatures which in turn releases more greenhouse gases such as CO_2, CH_4, and NO_2 from the terrestrial ecosystem, resulting a positive feedback loop in total GHG emission. On the other hand, photosynthesis is increased at a higher CO_2 level causing a negative feedback loop in terms of increasing global temperature due to GHG (van Nes et al., 2015),(Cramer et al., 2001). It is because photosynthesis process uses light energy, water and CO_2 to turn into chemical

[2]in a recent publication by van Nes et al. (2015) has empirically proven that GHG is indeed causing the rising of temperature with feedback effects

energy resulting in a reduction in CO_2 levels in the atmosphere. Also, at higher temperatures methane is released from the sea floor causing an increase in total greenhouse gas emissions in a positive feedback loop (Archer et al., 2009). The net increase in the amount of GHG in the atmosphere is causing catastrophic Climate Change. Its negative impact is wide in range and its affecting the inhabitants of the planet earth(Pachauri et al., 2014). Shifting of terrestrial organisms (Chen et al., 2011b), extinction of species, disrupted predator-prey and plant-insect interaction (Parmesan, 2006), habitat loss (Mantyka-pringle et al., 2012), biodiversity loss (Heller and Zavaleta, 2009), coastal upwelling (Bakun, 1990),Coral Reef Decline (Hoegh-Guldberg, 1999), acidification of the sea (Hoegh-Guldberg et al., 2007) are few of the many potentially adverse effects of Climate Change. Also from the economic perspective, climate change could play such a negative role that recently the chief of Bank of England warned that "global warming could become one of the biggest risks to economic stability in the future" (BBC, 2015). An increment of global temperature could also result in disease outbreaks such as the Zika virus spread through Aedes egypti mosquito bites, which has been linked with record high temperature in Brazil(Climate Action, 2016).Although the record high temperature is partially a result of 2015 El Nino, however, the spread of viral Dengue fever, carried out by the same mosquito host, throughout the South and Central America has been blamed on global warming (World Meteorological Organization, 2015), (Climate Action, 2016). In addition to that Hall et al. (2015) and Hoegh-Guldberg (1999) has pointed out that climate change is also "extremely significant" for tourism and it is negatively affecting the tourism industry. The behavioural pattern of tourists decision making is heavily influenced by environmental consequences of GHG and it has been argued that "Tourist perceptions of destination impacts and of the environmental consequences of travel will likely play a central role in travel decision-making" (Scott et al., 2008, p.20). However, it is important to mention that some influences on the tourist's decision making are mainly due to, somewhat unscientific reports widely spread by the media. To elaborate, for instance, a popular newspaper in the UK called The Guardian titled an article as "The likelihood [is] that Mediterranean summers may be too hot for tourists after 2020" and Rutty and Scott (2010) has criticised and argued that these kinds of bold statement in the media are an exaggeration of the fact (Guardian, 2006). Nevertheless, they have also acknowledged "The role climate plays in destination choice and its effects on tourist decision making remain understudied, an important knowledge gap" (Rutty and Scott, 2010, p.279). The authors also argued that media has very strong influence on the tourists and his study found that 52% of tourists would change their holiday plans before booking due to the media stories and in fact 28% would change their holiday plans even after the booking is done.

2.5 Carbon footprint measurement for tourism

Carbon footprint measurement is a widely used term when it comes to quantifying greenhouse gas emissions and this can be applied for tourism as well (Dwyer et al., 2010). However, besides carbon footprint's ubiquitous usage the definition of how to measure carbon footprint is not commonly agreed. It is usually defined that carbon footprint stands for "the certain amount of gaseous emissions that are relevant to climate change and associated with human production and consummating activities" and this is applied for a given activity, process or service(Wiedmann and Minx, 2008, p.2). Nonetheless, researchers dispute[3] on the measuring methodology and which gasses should be considered or should not to be considered besides carbon dioxide. In any-case calculating carbon footprint and identifying the effect of tourists on carbon emission are same. The key difference in this study and carbon footprint studies is here causal links between tourism and carbon emission are being investigated by using the already estimated data while in carbon footprint analysis for tourism GHG emission associated with tourism are being estimated based on theoretical knowledge (Wiedmann and Minx, 2008). The estimation based on theoretical evidence is not robust enough because the effect of tourism on a particular region could be different from another region due to not being able to understand the total impact of complex tourism dynamics on carbon emissions. To give an example, calculations of tourists consumption demand for goods and services that are imported into the economy is considered in carbon footprint measurement but the local industries also serve tourists and while serving the tourists the local industries also need to import goods and services(Munday et al., 2013). All these variables based on tourists consumption may vary widely from region to region .

2.6 Research Gap

It is clear that the tourism industry is very important in the modern economy and climate change is the biggest threat to our planet. The relation between tourism and greenhouse gas emissions, is also immensely important from both tourism and climate change perspectives. It is only recently that statistical causality analysis has been performed for investigating the link between tourism and greenhouse gas emissions. The literature review revealed three different research publications in journals closely related to this study (Lee and Brahmasrene, 2013),(Amzath and Laijun, 2014),(Ben Jebli et al., 2014). All these three studies have used Granger causality for detecting causal relation from tourism towards greenhouse gas emissions.

[3]In this study data for emission are overall emission measured by each individual governments by considering IPCC's national greenhouse gas inventory guideline as a standard

An Analysis of tourism-emission relations for the European Union, concluded that "Contrary to what many would expect that tourism would harm the environment, this study finds that increased tourism does not have to lead to increased CO2 emissions" (Lee and Brahmasrene, 2013, 74). The statement is very bold and concludes tourism in EU does not cause or contributes to emissions. However, in this study the total emission is considered rather than emission from several sectors and cases when Granger causality might produce a false negative result are not discussed. Similarly, in another study, Amzath and Laijun (2014) applied Granger causality for the Maldives and could not find enough statistical evidence that tourist arrivals are causally related to total carbon emissions. Lastly, Granger causality has been applied to the Central and South America region and as like the previous analysis did not find any short run causality, which is a Granger causal relation between tourist arrivals and CO2 emissions (Ben Jebli et al., 2014).

From the literature review, it appears that the three above mentioned studies are the only ones which have applied Granger causality for empirical causality analysis between tourism and emissions. Those studies are the most closely related to this research and none of the studies have found evidence that tourism causally influences carbon emissions. This goes against many other theoretical pieces of evidence suggesting the causality relation between tourism towards carbon emissions discussed in the earlier sections of this chapter. It is important to acknowledge that even carbon-temperature causality analysis using Granger causality did not produce any significance statistical evidence (van Nes et al., 2015)(Stern and Kaufmann, 2014). It is known that the greenhouse gas emission and temperature relation is widely accepted and established by not using Granger causality but other methods e.g.CCM (van Nes et al., 2015). As a result, it is very important to further investigate tourism-emissions because the policy makers would be looking into these research outcomes.

To investigate this relation further more research needs to be done and the following research gaps have been found and are considered in this area of tourism-emissions causality relation analysis:

1. In every tourism-emissions Granger causality analysis only total emissions are considered. Carbon emissions consist of several sectors(e.g. emissions from Agriculture, Waste Management). So far no research has been done to identify if tourists causes emissions from any specific sector besides total emissions.

2. Limitations associated with Granger causality have not been discussed.

3. Applicability of Granger causality analysis in this specific domain of Greenhouse gasses emissions and tourism has not been discussed.

4. Other causality detection methods(e.g. Converged Cross Mapping(CCM)) beside Granger Causality are not considered for further analysis.

5. There exist tourism carbon footprint models but the direct and indirect effects on sectors of emissions by tourism are considered without empirical evidence. This has been discussed in the tourism carbon footprint section.

Chapter 3

Methodology

In this thesis, two main methodological approaches have been used to infer statistical causality. They are namely,

1. Granger Causality
2. Convergent Cross Mapping (CCM)

Granger causality is developed by Clive W.J. Granger. His analysis of cointegration and causality has contributed for him to win Nobel Memorial Prize in Economic Sciences (Nobelprize.org, 2016). The second approach is called Convergent Cross Mapping (CCM), which is a method to detect causality based on theory nonlinear of dynamical system(Sugihara et al., 2012). This method has been developed by George Sugihara and first published in 2012 in journal Science (Sugihara et al., 2012). CCM is different from the Granger causality in many ways which are discussed later in this chapter.

3.1 Concept of Causality and Granger Causality

It is very common understanding that correlation does not mean causation and it is also not a necessary condition for causation (Sugihara et al., 2012). The major advancement of causality in statistical analysis happened in 1969 with the invention of Granger causality.The major difference between Granger causality and correlation is, Granger causality is based on perdition rather than being mere correlation[1] and since 1969 Granger causality has been used in different paradigms ranging from its original motivation econometrics to neuroscience, climate science and climate change(Granger,

[1]Prediction is the key difference between causality and correlation Berkeley (1874)

1969) (Ding et al., 2006) (Mosedale et al., 2006) (Kaufmann and Stern, 1997). There have been several studies conducted to identify the causal relation between carbon dioxide concentration and global mean temperature using Granger causality (Triacca, 2005). However, it's important to mention that like many statistical analysis methods the applicability of Granger causality in carbon-temperature causal relation has been criticised by some of the researchers e.g. Triacca (2005). Not surprisingly Granger causality has also been used to identifying causality between tourism and GHG emission (Lee and Brahmasrene, 2013) (Amzath and Laijun, 2014). However, it is only very recently that Granger causality has been applied in this domain of tourism and GHG emissions to identify the specific influence of tourists on GHG. In every case, Granger causality has been applied to identify causality between tourism and overall emissions whereas in this study Granger causality is applied to different sectors of GHG emission.

3.2 limitations of Granger Causality

Granger causality was mainly developed for linear stochastic processes, and the core idea is if a time series variable x Granger causes y then the past values of x should increase the predictability of y (Granger, 1969). Details of this method are discussed later in this chapter. Granger causality is tested by estimating statistical models using the variables of interest. After estimating the model variables are excluded from the model to see how it statistically effects the predicting power of other variables. If it does then the removed variable is considered as causal to the remaining effected variable(Sugihara et al., 2012). As a result, this approach requires that the causal variable(s) be able to completely removable from the model. In other words, Granger causality requires variables to be separable which implies that when the causative variable x is totally removable from the model or system only then it can be robustly tested if it has a causative effect on the other variable y (Granger, 1969). The issue of separability is often not satisfied especially in deterministic dynamical system (Sugihara et al., 2012). That is, while Granger causality is workable for the linear stochastic system but it could fail to identify the true underlying causal structure if the issue of separability is violated (Takens et al., 1981)(Deyle and Sugihara, 2011). To give an example, in a recent study, it has been argued that indeed GHG and temperature are nonlinear dynamical system (van Nes et al., 2015). Although there exists few nonlinear Granger causality tests such as kernel-Granger causality but Sugihara et al. (2012) argued that even for these nonlinear methods the issue separability is not satisfied (Marinazzo et al., 2008). In addition to that according to Stern and Kaufmann (2014) there are a few other possibilities which might result in the failure of identifying the actual causal relation and they are noise and poor estimation of the data, Lack of frequent data, small sample size, omitted variable bias, failure to identify appropriate lag, and effects of different causal channels cancelling each other.

3.3 Convergent Cross Mapping(CCM)

Sugihara et al. (2012) invented the Convergent Cross Mapping (CCM) method for causality detection. CCM could be argued as an equation-free approach for detecting causality (Sugihara et al., 2012). A major benefit of this method is that is, robust to unmeasured confounding variable which could result in spurious causal association (Maher and Hernandez, 2015). CCM is based on the theory of deterministic dynamical system and more specifically an implementation of Taken's theorem (Takens et al., 1981)(Deyle and Sugihara, 2011). One of the fundamental difference between Granger causality and CCM is that, Granger causality uses the causal variable to predict the caused one, on the other hand CCM looks into the affected variable to predict the causal variable Sugihara et al. (2012). CCM has also been shown to be able to identify the actual direction of the causal relation even in case causal feedback loops (Maher and Hernandez, 2015)(van Nes et al., 2015). When first introduced CCM was used to successfully solve the controversial sardine-anchovy-temperature problem in the California current. Sardine and anchovy are saltwater fishes and it had been a long debate whether the population of these two types of fishes is causally related. Solving a half a century debate, Sugihara et al. (2012) showed that sardine and anchovy are not dynamically coupled, but that temperature is coupled with both sardine and anchovy numbers. CCM has also been used in other areas to prove that galactic cosmic rays effect temperature on short inter-annual timescales but there is no proof that it has an effect on the global warming trend of recent years (Tsonis et al., 2015). CCM has a strong appeal for being able to be used as a diagnostic technique in order to help early detection of dementia (McBride et al., 2015). So far only Granger causality is being used in medical science to find causal relations by assuming that the system is linear and the interaction is not complex whereas de Jonge and Roest (2014) argued that many relations in medical science variables tend to be nonlinear and complex. For instance, physical activity and depressive symptoms could interact with each other such that someone who does not do exercises regularly has a greater chance to develop his or her mood by doing exercise than someone who does regular exercise. In addition to that, the relation between exercise and mood could be bidirectional (de Jonge and Roest, 2014). Understanding of the mechanism of reading by using eye movement has also its application(Wallot, 2014). Identification of the long-term effects on the grassland dynamics driven by increasing dryness has also used CCM (Brookshire and Weaver, 2015). Also, Fan et al. (2014) have used CCM and suggested that dust storms in Inner Mongolia are negatively affected by earlier vegetation in the predicted future due to global warming. Dost (2015) has used CCM to investigate the causal link between marketing channel systems and economic systems. Also, there is a strong urge to use this method in order to detect causality from complex data with relation to a human in the field of proteomics(large scale study of protein)(Sauer and Luge, 2015). This is because of the complexity of the data and CCM's ability to detect causal structure from complex data of protein structure. In recent days the advancement of social networks such as Twitter, Facebook provides unprecedented opportunity to study social interaction and CCM also been applied and promoted in order to understand the underlying complex causal structure of the social media (Luo et al., 2014). Heskamp et al. (2014) discussed CCM as a promising technique for cerebral autoregulation estimation due to its suitability for nonlinearity. Cerebral autoregulation is a physiological mechanism which regulates the cerebral blood flow velocity to keep it constant in a relative amount without being affected by the change in arterial blood pressure. There is strong indication that the usage of this method in bio-medicine as Maher and Hernandez (2015) discussed mainly due to its ability to detect causality in complex, nonlinear system. Perhaps, most related to this analysis, in one recent study van Nes et al. (2015) applied CCM in the domain of greenhouse gas and temperature. The study result is strongly suggestive that the earth's temperature is driven by the internal mechanism, over glacial and interglacial time scales. In addition to that, they have identified a feedback effect from temperature change to the concentration of greenhouse gas.

3.4 limitation of Convergent Cross Mapping (CCM)

One of the main limitations of CCM is it requires long time series data, typically $>= 30$ or $>= 25$ time series observations (Sugihara et al., 2012) (Maher and Hernandez, 2015). However, recently Clark et al. (2015) published another method called MultispatialCCM which is applicable for time series of even fewer than five observation by considering data from multiple spatial replications of the process. This method has been developed by combining CCM and dewdrop regression. This MulitspatialCCM has been applied in simulated and real ecological data and showed that it can successfully identify causal relation (Clark et al., 2015). However in real life, not all the process could have multiple replications. Also, there is another modified version of CCM developed by combining CCM and neural network called Cross Map Smoothing(CMS). CMS has been shown to be successful for time series data as low as 20 observation (Ma et al., 2014). Cross map smoothing (CMS) is relatively less applied in the scientific community in fact, probably only applied in its original publication to date. Another limitation is, the domain of CCM's applicability remains an open question (McCracken and Weigel, 2014). A few of the test examples done by McCracken and Weigel (2014) showed that CCM is inconsistent with the intuitive notion of driving (one causal variable driven by another one) and they have proposed a modification of CCM called pairwise asymmetric inference (PAI). Another limitation of the convergent cross mapping is it might not be able to identify causal relation properly if there is a strong forcing from an external variable that overwhelms the targeted relationship's dynamics (Maher and Hernandez, 2015). Most importantly CCM cannot be applied if the system is purely stochastic[2] or random and linear like white noise (Sugihara et al., 2012), (Maher and Hernandez, 2015), (Clark et al., 2015). However, because observational noise exists in almost all kind of data, it is important to state that Takens theorem, the theoretical basis of CCM, is still valid even if there exists observational noise in the stochastic process or in other words where the deterministic skeleton is driven by stochastic process (Sugihara, 2015a).

3.5 Applicability of GC and CCM for Tourism and Carbon Emission

Our only focus is on time series data for this research. We have time series variables for tourism and greenhouse gas emission. Granger causality is a heavily model based approach and is applicable in multiple models like VAR(Vector Auto Regression), VEC(Vector Error Correction), and kernel models (Sugihara et al., 2012) (Marinazzo et al., 2008) (Masih and Masih, 1996). Granger causality is not applicable if the time series data are non-separable and non-linear(Sugihara et al., 2012)(Clark et al., 2015). Although there exists non-linear versions of Granger causality but the issue of non-separability , as discussed in section 3.2, remains. If this issue of non-separability exists in our focused time series data of tourism and greenhouse gas emission than the result of Granger causality might not be robust.

Studies have used VAR Granger causality, the linear version of Granger causality in this domain of tourism and GHG and their work has been published in journals like tourism management,without considering the non-linearity or non-separability issue (Lee and Brahmasrene, 2013). To investigate further by intending to make this study robust enough CCM is also considered for this research. As far as the CCM method goes, this should be applied only if the time series is non-linear (Clark et al., 2015). The test for non-linearity is being done using one of the two nonlinear forecasting methods called S-map or Simplex-projection (Sugihara, 1994) (Sugihara and Mayf, 1990). In addition to that if the data is very noisy CCM might not return a good result, however, Sugihara

[2]although some series might appear e.g. white noise but the underlying data generating process might be governed by a deterministic dynamic system in some higher dimensional space (Sugihara, 2015b)

et al. (2012) stated that it showed the good result when applied to data as noisy as fisheries.

CCM could applied because of the variable time lag and it is argued that variable time lag is indicative of a deterministic non-linear system (van Nes et al., 2015). In case of tourism-emissions causality, the effect of tourism on emissions could have variable time lags.

In a publication for relating vegetation and dust Storm has applied CCM (Fan et al., 2014). However in the same study linear regression also been used. CCM has been chosen due to the synergistic effects between the variables(Fan et al., 2014). Synergistic effects mean the total effect of two variable causing each other should have a higher effect than their total sum and the outcome is not linear. So, having synergistic effects is indicative of nonlinearity and CCM could be used besides using linear methods like linear regression. The relation between greenhouse gas emission and tourism has a strong indication of having synergistic effects. For instance transportation emission from tourism should be linked to how many vehicles are being used by tourist. More tourists do not mean more vehicle in a linear way in most of the cases. For instance, a tourist bus could emit the same amount of carbon just as a small car whereas tourist bus can have as many as 50 tourists or more than that and an SUV can have only around 7-8 passengers at most. In most of the cases, tourists prefer public transportation rather than hiring private one due to affordability Albalate and Bel (2010). In the case of using large public transport like a train, the relation between tourists and usage of the train is complex Page (1994). Another fact is sectors like industry and business should have the effect of tourists in terms of emission on a variable time scale.

3.6 Granger Causality

Granger causality is based on two basic assumptions (Granger, 1969):

1. The cause happens before its effect
2. The cause contains independent information which can predict its effect.

Granger causality testing is usually a heavily model based approach. In this research Granger causality is tested via a widely used approach called Vector Autoregression or VAR Granger causality test (Triacca, 2005). Vector Autoregression models are multivariate autoregressive linear models, a commonly used model in order to capture the dynamics of a system evolving over time (Giannone et al., 2015) (Toda and Yamamoto, 1995). In a VAR model it is not essential to know the true underlying structure of the data generating process rather it empirically captures the correlation and dynamics of the system and a VAR model does not require a priory assumptions like structural equation models (Brandt and Williams, 2007).A VAR model using 2 time series variables is consist of two equations where each of them includes one endogenous variable and its own lag values and other variables' lag values as exogenous variables. The appropriate lag order is selected based on the *fitness* of the model or prior knowledge of the system.

3.6.1 Vector Auto Regression(VAR) Model

A $VAR(p)$ is a VAR model which includes variables of p lags. A $VAR(1)$ model in matrix format using two-time series variables X and Y is expressed via the following equations (Chen et al., 2011a).

$$\begin{vmatrix} X_t \\ Y_t \end{vmatrix} = \begin{vmatrix} \alpha_x \\ \alpha_y \end{vmatrix} + \begin{vmatrix} \beta_{xx} & \beta_{xy} \\ \beta_{yx} & \beta_{yy} \end{vmatrix} \begin{vmatrix} X_{t-1} \\ Y_{t-1} \end{vmatrix} + \begin{vmatrix} \epsilon_{xt} \\ \epsilon_{yt} \end{vmatrix} \tag{3.1}$$

In equation format $VAR(1)$ model can be written as:

$$X_t = \alpha_x + \beta_{xx} X_{t-1} + \beta_{xy} Y_{t-1} + \epsilon_{xt} \tag{3.2}$$

$$Y_t = \alpha_Y + \beta_{yx} X_{t-1} + \beta_{yy} Y_{t-1} + \epsilon_{yt} \tag{3.3}$$

In equation 3.2 the X is the dependent variable and Y is the independent variable. In a VAR equation, the dependent variable X is called the endogenous variable and Y which is the independent variable is called the exogenous variable. The ϵ_{xt} and ϵ_{yt} are the error terms of two of these equations. In the first equation, as we can see the X could depend on the dynamics of its previous lag X_{t-1} and the exogenous variables' previous lag Y_{t-1} in the system. α_x , β_{xx} and β_{xy} are the coefficients. These coefficients are the estimations needed to perform based on the data set of the application and the estimation is being done through ordinary least squares estimation. The second equation is the same as the first equation except the exogenous Y is now the endogenous variable and x is used as an exogenous variable. This two equation together they are called a $VAR(1)$ model. The number 1 stands for allowing one lag for the various variables(including lag of the endogenous, exogenous). These two equations are two $AR(1)$ processes which allows own lag and lag of another variable in the model. Because it has two or many variables in the system in two equation its called the Vector $AR(1)$ models which the $VAR(1)$ model. Depending on how many lags are included in a VAR model its called a $VAR(p)$ model where p denotes the number of lags that effects the system.

A VAR model could be estimated using ordinary least square(OLS) method because a VAR model does not require to estimate all the equations at the same time because all the equations could be considered as unrelated in current time because they only allow lagged exogenous variable of the other time series (Tsay, 2005). If there are no restrictions on the coefficients of the models using multiple OLS regressions the VAR model could be estimated and for each of the dependent variables one OLS is used to estimate the model (Tsay, 2005).

3.6.2 Stationarity

Before estimating a VAR model all the time series variables are required to be stationary in order to avoid spurious regression. To say if a time series to be stationary are the following conditions needs to be valid (Granger, 1969) (Brandt and Williams, 2007) (Fernandez, 1981).

1. $E[x_t] = \mu$
2. $Var(x_t) = \sigma^2$
3. $Cov(x_t, x_{t+h}) = f(h) \neq g(t)$

The first condition means the expectation of a process needs to be constant μ which is not a function of time. The second condition is the variance of the series is also a constant σ^2. The final assumption is the covariance of a process at time t and after $t+h$ needs to be a function of h but not a function of time. That means the covariance or structure of a process does not change with time and its purely stochastic. That means the process is coming from one single data generating process throughout the time.

A process needs to be stationary in order to estimate VAR model because the linear relationship in the VAR model does not hold for all the time if the processes are non-stationary. It is not possible to estimate the coefficients if the process is changing over time in a different rate (Manuca and Savit, 1996). Also, if the processes are stationary it simplifies the law or large number and allows us to apply the central limit theorem. These two laws are essential in order to do statistical inference soundly (Manuca and Savit, 1996). Harvey et al. (1986) showed that if variables are not stationary it can run into the problem of spurious regression or relation. Even if two series are not related and they are non-stationary if OLS is used to estimate and regress one stationary variable with another non-stationary variable the R-Squared value could be very significant.

$$R^2 = 1 - \left(\frac{ExplaindVariation}{TotalVariation} \right) \tag{3.4}$$

The R-Squared is the goodness of fit of a linear model in the data. In the case of non-stationary variables, it is possible to have a higher value of R^2 when they are regressed on one another even though there is no relation. This high R^2 is only due to the existence of the similar kind of trends in same or opposite direction (Harvey et al., 1986).

If a variable is non-stationary it is possible to make it stationary by differencing the time series with its lagged values (Phillips, 1987). If a time series is y_t the stationary time series could be:

$$y_t^l = y_t - y_{t-l} \tag{3.5}$$

Here, l is the number of difference order. The time series is performed differencing in increasing order until it becomes stationary. In building a var model, all the time series are performed differencing in the same order of the highest required difference order of any of the series. If a VAR is estimated using two time series variables x and y and it has been found that x is first order but y is second order stationary then it requires to performer deference x and y both in second order. To test a time series whether its stationary or not there are various tests available. One of the widely used tests is the Augmented Dicky Fuller test (DeJong et al., 1992). This test has a null of having unit root in the process. When a time series contains unit root then its non-stationary. If there is not enough statistical evidence to accept the null of unit root the alternative of not having a unit root is accepted and it is inferred that the process is stationary.

To demonstrate the reason behind non-stationarity due to unit root lets consider an auto-regressive process with 1 lag, $AR(1)$ (Cheung and Lai, 1995).

$$X_t = \rho X_{t-1} - \epsilon_t \tag{3.6}$$

Here the error term or residual tend to be independent and identically distributed (i.i.d) having mean 0 and variance σ^2.

In a stationary process ρ is less than 1. The conditional expectation of the series is,

$$E[X_t|X_{t-1}] = \rho X_{t-1} \tag{3.7}$$

It can be seen from the equation 3.6 that if ρ is less than 1 there will be a pressure which will drive a process towards the mean but if its 1 or unit root is present than there will be pressure which will drive the process towards the mean-line. The is an intuitive demonstration to show that if a series has unit root then its not stationary.

The Dicky Fuller test is performed by statistically testing if ρ is < 1 or is 1. For testing if a $AR(1)$ series is stationary the following null and alternative hypothesise for ρ is used .

$$H_0 : \rho = 1, H_1 : \rho < 1 \tag{3.8}$$

If the null hypothesis is true which is presence of unit root in equation 3.5 both X_t and X_{t-1} are non-stationary . In such situations the central limit theorem does not apply so its not possible to performe ordinary t-statistics. To solve this X_{t-1} is substituted from the both side of the equation 3.5:

$$X_t - X_{t-1} = (\rho - 1)X_{t-1} - \epsilon_t \tag{3.9}$$

In this equation 3.9 if the null hypothesis is true which is $\rho = 1$ and the term $(\rho-1)X_{t-1}$ will not exists on the right side, as a result, the $X_t - X_{t-1}$ becomes stationary and it becomes possible to apply normal t-statistics and in another case if the null < 1 the null of stationary is accepted. The equation 3.9 can be re-written as:

$$X_t - X_{t-1} = \delta a X_{t-1} - \epsilon_t \tag{3.10}$$

Even though, the value of δ does not have at distribution when the asymptotic theory is applied because X_{t-1} is not stationary. To solve this problem the t statistic is being calculated and then it's compared with the Dicky-Fuller distribution which is valid for this test. This test is for simple $AR(1)$ process and when the series is in higher order $AR(p)$, $p > 1$ the following $AR(p)$ equation is being estimated.

$$\vec{\Delta} = \alpha + \delta X_{t-1} + \sum_{i=1}^{p} \beta_i \Delta X_{t-i} \tag{3.11}$$

To include the lag orders to model a more complicated process than $AR(1)$ the following steps are being done:

1. Increase lag order and test are performed for each of the Δ terms using t distribution until they become insignificant.

2. Test if the residuals have serial autocorrelation or not. And increase the lag order until auto-correlation is solved

3. Using information criteria like AIC and SC to select lag order to build $AR(p)$ model.

Once the model is estimated which describes the series then the test is performed for unit root the same way it was tasted for a $AR(1)$ process.

3.6.3 Lag Order

The optimal lag order p could be selected by calculating the auto-correlation between the error terms of the residuals in the equation (Toda and Yamamoto, 1995). If they are auto-correlated the lag order is increased until the auto correlation is solved. A good estimation of a model requires the residuals to be white noise (Goebel et al., 2003). Another way to select lag order is to test for the lowest optimal lag order using different lag selection criteria such as Akike(AIC), Schwarz(SC) information criterion (Brandt and Williams, 2007). If a VAR model has $\bar{\epsilon}$ and ϵ vectors of residuals the log-likelihood value is:

$$log - likelihood = -\frac{TK}{2}(1 + \log 2\pi) - \frac{T}{2}\log D \tag{3.12}$$

here:

$$D = det\left(\frac{\sum_t \epsilon\bar{\epsilon}}{T}\right) \tag{3.13}$$

If n is the number of estimated parameters, The information criteria AIC is computed by

$$AIC = -\frac{2l}{T} + \frac{2n}{T} \tag{3.14}$$

And Schwarz information criteria is computed from the following equation:

$$SC = -\frac{2l}{T} + n\log\frac{T}{T} \tag{3.15}$$

3.6.4 Cointegration

As it was discussed that its not a good idea to regress a non-stationary process with one another or estimate a VAR model but there is one exception. If two time series variables distances from each other are constant throughout time after multiplying one of them with a constant parameter then there might exist a non-spurious relation between two of them although they are non-stationary. If one series is X_t and another one is Y_T if $y_t - \beta X_t = I(o)$ then it can be said that these two series might have statistically significant relation and this idea of having relation with two non-stationary series is called cointegration (Hall et al., 1992) (Granger, 1986).

In order to test if there exist a parameter β a test is performed which is called the Engle-Granger two-step method (Kremers et al., 1992) (Hall, 1986). The first step is to build a simple linear regression model with the two parameters using OLS estimation.

$$Y_t = \alpha + \beta X_t + \mu_t \mu_t = Y_t - \alpha - \beta X_t \tag{3.16}$$

$$\mu_t = \delta_o + \delta_1 \mu_{t-1} + .. + V_t \tag{3.17}$$

From 3.16 equation it is possible to get the estimated residuals μ and the test is performed using Dicky-fuller test to see if its stationary or not. But the parameters are estimated in 3.16 rather than using actual observed value but a more strict amended dicky-fuller distribution is used to compare with the T statistics. It can only be tested for co-integration if there exists an actual value for β which is not 0 and here the null hypothesis is $\beta = 0$ meaning that there exists no relation between Y_t and X_t. If only there is enough evidence to accept the null than further test for the stationary in the residuals is performed.

3.6.5 Vector Error Correction(VEC) Model

If two variables are co-integrated its an implication that they have long run association and Vector Error Correction(VEC) model can be estimated in the level of data. In this case, the conventional asymptotic theory will still be valid for hypothesis testing even if the variables are not stationary in the level (Toda and Yamamoto, 1995). In VEC models long run relations are also considered besides short run dynamic relations.The co-integrated test is done only if variables of interest are stationary in the same order. Below is the equations for Vector Error Correction model(VEC) model for lag 1.

$$\Delta X_t = \alpha_x + \beta_{xx} \Delta X_{t-1} + \beta_{xy} \Delta Y_{t-1} + \epsilon_{xt} - \lambda_x \left(Y_{t-1} - \alpha_o - \alpha_1 X_{t-1} \right) \tag{3.18}$$

$$\Delta Y_t = \alpha_Y + \beta_{yx} \Delta X_{t-1} + \beta_{yy} \Delta Y_{t-1} + \epsilon_{yt} - \lambda_y (Y_{t-1} - \alpha_o - \alpha_1 X_{t-1}) \tag{3.19}$$

In the VEC models the equation with λ defines the long-term association between the two variables X and Y.

3.6.6 Auto-correlation in the Residuals

After setting up VAR model it is necessary to make sure that the model is sound. A VAR model could be a very powerful model if there is no serial correlation in the residuals even though its residuals are correlated with variables due to the immediate effect. To test for autocorrelation in the different time lags for the residuals the methods called Portmanteau autocorrelation test and Godfrey Lagrangian multiplier (LM) serial correlation test is being used (Engle et al., 1984) (Godfrey, 1978). The second test, in short, is called the LM test.

The main idea of this LM test is regressed is performed on the residuals on its higher order and it is tested if the process is $AR(0)$ or not. But in a VAR model, there are endogenous variables which invalidate the T or F-statistics, as a result, an artificial VAR model is estimated where lags of residuals as endogenous variables are considered as well. In one model higher order of residuals are allowed and in another, they are not allowed and then the test is performed using $\chi^2 LM$ statistics to see if its the case that the residuals with higher orders model are significant enough or not.

Bellow is the equation of unrestricted VAR of the residuals

$$\epsilon_t = Y_{t-1}\alpha_1 + ... + Y_{t-l}\alpha_l + \epsilon_{t-1}\beta_1 + ... + \epsilon_{t-p}\beta_p + \mu_t \tag{3.20}$$

So in this model, it is assumed that the residuals are correlated so β is estimated.

Also, another model is estimated which is the restricted one where all the β equals 0, as a result, it is assumed that there is no serial correlation in the residuals. That means the past values of the residuals does not define the current values.

$$\epsilon_t = Y_{t-1}\alpha_1 + ... + Y_{t-l}\alpha_l + \bar{\mu}_t \tag{3.21}$$

Now residual covariance is constructed for equations 3.20 and 3.21 respectably COV_{unres} and COV_{res}

$$COV_{unres} = T^-1 \sum_{t=1}^{T} \mu_t \bar{\mu}_t \tag{3.22}$$

$$COV_{res} = T^-1 \sum_{t=1}^{T} \mu_t \bar{\mu_t} \tag{3.23}$$

After that the LM statistics is formed and compared with the χ^2 distribution.

$$LM = T[q - trace(COV_{unres} COV_{res}^- 1)] \tag{3.24}$$

Here the number of endogenous variables are q and $trace$ is the trace operation. The null is there is no serial correlation. Mathematically it can written as:

$$H_o = E[\epsilon_t, \epsilon_{t-p}] = 0p = 1, .., h \tag{3.25}$$

here $E[\epsilon_t, \epsilon_{t-p}]$ is the covariance of residuals at lag t and $t - p$.

Another method to test for serial correlation is the portmanteau test. The modified version of Q statistics is

$$Q_h = T^2 \sum_{j=1}^{T} \frac{trace(\overline{sc_j sc_0}^{-1} sc_j sc_0^{-1})}{T - j} \tag{3.26}$$

Here sc is the sample covariance matrix of the residuals. This distribution is χ^2 with large sample size with $q^2(h-n)$ degrees of freedom. q is the total number of endogenous variables.

3.6.7 Granger Non-causality

To test for Granger causality in the VAR model where there are multiple approaches available, in this case of a VAR model in equation 3.2 and 3.3 where there is a $var(1)$ model using time series variables X_t and Y_t the requirement is to find if variable X_t has enough information to linearly predict the future values Y_t where X_t is exogenous. This is the question required to answer if it is to be concluded that there is a causal relation or perhaps more specifically Granger causal relation between X_t and Y_t and also the other way around. In order to describe the Granger Causality test in more general terms lets consider the following equations (Granger, 1988b) (Granger, 1988a) (Granger, 1980)(Sugihara et al., 2012):

$$X_t = a_0 + \sum_{l=1}^{m} a_l X_{t-l} + \sum_{l=1}^{m} b_l Y_{t-l} + \epsilon_{1t} \tag{3.27}$$

$$Y_t = b_0 + \sum_{l=1}^{m} b_l X_{t-l} + \sum_{l=1}^{m} c_l Y_{t-l} + \epsilon_{1t} \tag{3.28}$$

It can also be said inversely if X_t Granger causes Y_t than the coefficient of the past values of Y_t in equation 3.27 which are b_l is non zero up to m. In this VAR Granger causality test the null is not Granger causing as a result it is called Granger non-causality test. The null and alternative hypothesis could be written as:

$_o$: Y_t does not have enough information for predicting X_t which means $b_1 = b_2 = .. = b_m = 0$, Granger non-causality

$H_{alternative}$: Y_t have enough information for predicting X_t which means $b_1 \neq b_2 \neq .. \neq b_m \neq 0$, Granger causality

To test the null hypothesis two VAR models are being estimated. One is by restricting by making all 1 to $m, b = 0$ and in another way, the variable Y_t is excluded from the model. As a result the models unrestricted and restricted will be:

1. Unrestricted (same as 3.27, $b_1 \neq b_2 \neq .. \neq b_m \neq 0$):

$$X_t = a_0 + \sum_{l=1}^{m} a_l X_{t-l} + \sum_{l=1}^{m} b_l Y_{t-l} + \epsilon_{1t} \tag{3.29}$$

1. Restricted ($b_1 = b_2 = .. = b_m = 0$)

$$X_t = a_0 + \sum_{l=1}^{m} a_l X_{t-l} + \overline{\epsilon_{1t}} \tag{3.30}$$

To test statistically the difference in residuals of these two models, residuals sums of squares, RSS for the two models are computed.

$$RSS_{restricted} = \sum_{t=1}^{T} \epsilon_{1t}^2 \tag{3.31}$$

$$RSS_{unrestricted} = \sum_{t=1}^{T} \overline{\epsilon_{1t}}^2 \tag{3.32}$$

Now the result is tested using wald statistics. It can also be tested using f statistics but in this analysis case, wald statistics is being used (Halicioĝlu, 2003) (Toda and Phillips, 1993).

3.7 Convergent Cross Mapping

Convergent Cross Mapping (CCM) is based on the theory of non-linear dynamics. It is possible to reconstruct the dynamic model from a time series using state space reconstruction technique (Sugihara et al., 2012)(Ye et al., 2015b). This is based on the fact that a time series could be considered as a projection of a dynamical system. If the real life data generating system is considered as a deterministic dynamical system the whole system could be compared as an attractor in higher dimensional space where each of the axis is influential variable in the system. In that attractor each of the points is a vector define as a specific temporal state and the temporal evolution are the trajectories of the attractor evolving over time in a nonstochastic manner. Although the system is very sensitive to its initial condition but the geometric shape of the attractor will hold essential properties of the system.

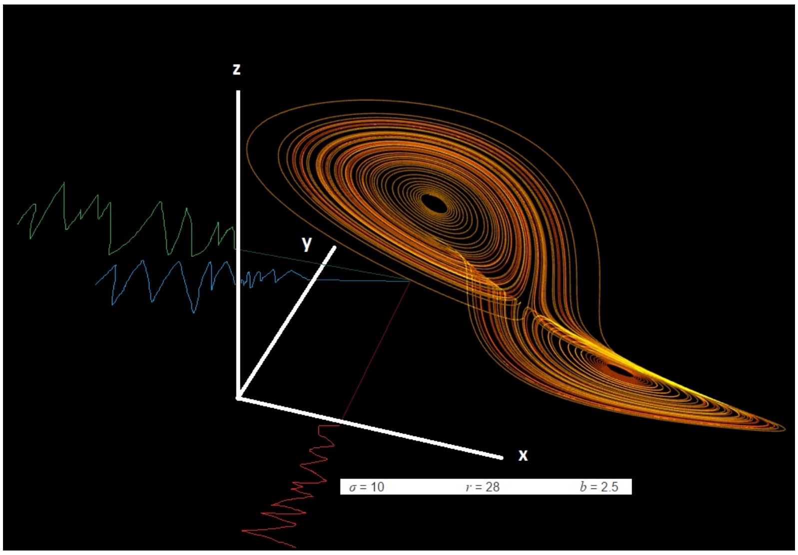

FIGURE 3.1: State space reconstruction for CCM

In the figure is shown a Lorenz attractor. In a three-dimensional space projection from the attractor to each of the axis X, Y, Z produces three different time series of the same system. Projection of a state from the attractor on one particular axis produces the state of the system on that axis and sequential projection creates the time series. Different projection on different axis creates different time series.

In case there exists all the time series one should be able to recreate the original attractor by projecting back to the three-dimensional space in the figure. This reconstruction could also be done just by looking at a single time series and the reconstructed attractor will hold essential mathematical property of the original attractor. This reconstruction is a based on Taken's theorem which states that it is possible to produce a shadow version of the original attractor just from one-time series by using different lags of the time series and projecting them back in higher dimensional space (Takens et al., 1981)(Deyle and Sugihara, 2011). This reconstructed attractor maps one-to-one with the original attractor. However, the true embedding dimension of the system also needs to be known. The best embedding dimension of the attractor is determined by evaluating the attractor's predicting skill for different embedding dimensions. The prediction is done by using simplex projection a nonlinear forecasting algorithm developed by Sugihara and Mayf (1990). This technique works only if the time series is coming from a nonlinear deterministic dynamical system. The test for deterministic nonlinearity is done also by using simplex projection. Using simplex projection the gradual degradation of forecasting skill implies that the trajectories are independent enough and the singularity is removed (Schiecke et al., 2015)(Sugihara et al., 2012)(Ye et al., 2015b). It is because in a deterministic chaos the trajectories of the attractor will eventually diverge limiting long term forecasting skill. If decreasing forecasting skill is observed while performing prediction for increasing step size non-linearity could be assumed for the system. After successfully reconstructed attractor for two time series the CCM algorithm is applied to test for causality.

Let's assume that X and Y are two time series variables and they are deterministic nonlinear. If a variable X is causal to another variable Y, then information about X should be encoded into the variable Y. This is one of the fundamental difference of CCM with Granger Causality. Granger causality is based on removing the cause X to see if the predictability of effect Y is reduced whereas CCM looks on to the affected variable to see if the causal variable is predictable. By taking the lagged value of the affected variable, Y shadow version of the original manifold which governs the dynamics of Y is reconstructed. This shadow reconstructed manifold will map one-to-one with the original manifold and its diffeomorphic to the original manifold. Which means the reconstructed manifold contains important mathematical property of the original manifold. From the reconstructed shadow manifold of Y if it is possible to predict the time series of X than CCM concludes Y is indeed caused by X. Here to test the predictability the nearest neighbour method called simplex projection is used. In order to differentiate between correlation and causation, a measurement of convergent is used. All the time series is not used at the beginning of the prediction from the reconstructed manifold of Y to X. The length of the time series is called library size. With small library size which is the length of time series, the predictability is tested with increasing library size. If a convergent is observed of predictability with respect to library size to some plateau than it becomes indicative of causation from X to Y.

An algorithm is provided bellow:

L is the time series length or library size
Time series variable 1, $\{X\} = \{X(1), X(2), ...X(L)\}$
Time series variable 2, $\{Y\} = \{Y(1), Y(2), ...Y(L)\}$
M_x, M_y are two manifolds
$\bar{M_x}, \bar{M_y}$ are the shadow constructed manifolds of X, Y
τ = time lag
$\hat{X}(t)|\bar{M_y}$ = estimating variable X from cross mapping using $\bar{M_Y}$

Step 1: Form vectors by taking lagged coordinates of {Y}, $y(t) =< Y(t), Y(t-\tau), Y(t-2\tau), ..., Y(t-(E-1)\tau) >, t = 1+(E-1)tot = L\tau....\ t = 1+(E-1)$ to $t = L$. This is our reconstructed manifold $\bar{M_y}$ and E is the embedding dimension

Step 2: Locate contemporaneous lagged coordinate vector on $\bar{M_Y}$ for each t, y(t) and find its E+1 nearest neighbors.

Step 3: Denote each of the time indices from closes to farthest of $y(t)$ by $t_1, ..., t_{E+1}$

Step 4: Estimate for $i = 1...E+1$

$$\hat{X}(t)|\bar{M_y} = \sum w_i Y(t_i) \tag{3.33}$$

Where for , $j = 1...E+1$

$$W_i = \frac{u_i}{\sum u_j} \tag{3.34}$$

Where

$$u_i = e^{-\frac{D[x(t),x(t_i)]}{D[x(t),x(t_1)]}} \tag{3.35}$$

Here D is the Euclidean distance

If the variables are dynamically coupled then nearby points in $\bar{M_x}$ could be able to identify nearby points in $\bar{M_y}$, thus they are causally related and X causing Y. This whole process is done with smaller library size L to increasing library size. When the library size increases the $\bar{M_x}$ becomes more dense and the nearby $E+1$ points shrinks and $\hat{X}(t)|\bar{M}_y$ should converge to $X(t)$. This is to identify causality from X to Y , in the case of determining causality from Y to X the method is analogous to the above one.

As discussed earlier one important issue is to see if the manifold is perfectly unfolded from the singularity. In CCM the embedding dimension E is more important than the attractor dimension d. The embedding dimension and the attractor dimension is related to the Whitney's theorem, $E \leqslant 2d + 1$(Sugihara et al., 2012, sup). Each of the embedding dimensions, E could imply each forcing variables. Each of E dimensions could produce one times series which is basically the projection of the attractor on that plane. Another outcome of state space reconstruction is, by analysing how many E dimensions are required for the state space to embed a d dimensional manifold it is possible to approximate the number of influential variables operating within the system. This identification could help to build a better model.

3.8 MultispatialCCM

Multispatial CCM is a modified version of CCM (Clark et al., 2015). CCM requires roughly around 30 data points for successfully causal relation detection. This method multispatial CCM combines dewdrop regression with CCM to allow the detection causal relations with shorter time series but with multiple spatial replications. It samples much short time series from the observed spatial replication of the time series in order to conduct the test.

This algorithm follows five steps which are described below:

1. The best embedding dimension is selected using simplex projection. The forecasting varies with respect to different embedding dimension. The embedding dimension is selected by plotting by plotting predictability with respect to the embedding dimension, E.

2. This step is to determine if the series is deterministic non-linear not purely random. This test is done by forecasting future values by using historic values of the time series. Here also, simplex projection is used and if the series is deterministic nonlinear the predictability should decrease while time steps increase.

3. CCM algorithm is applied discussed in the previous section. In multispatialCCM cross correlation is tested not only with one of the time series but also on the replications of the time series in the composite series.

4. Non-parametric bootstrapping is being used in order to remove the bias due to the different order of replication. N Sample is being drawn from all the spatial

replicates and all the all the previous steps are repeated. This process of sampling is done for many iterations.

5. In the final step the rise of calculated prediction, ρ is calculated with respect to library size L to see if there is an increase in the prediction or not.

Chapter 4

Results

4.1 Granger Causality approach

Granger causality test has been applied in the time series data for UK and Australia. In this test of Granger causality, the null hypotheses are those non-causal relations. The null hypothesises are written bellow:

1. Tourist number does not Granger cause greenhouse gas emission from different sectors of emission for the UK
2. Tourist number does not Granger cause greenhouse gas emission from different sectors of emission for Australia
3. Tourist number does not Granger cause greenhouse gas emission from total emission for the UK
4. Tourist number does not Granger cause greenhouse gas emission from total emission for Australia

All the series are log transformed to reduce the variability in the data and it shapes the data more close to the normal distribution.

4.1.1 Granger non-causality test results for UK

4.1.1.1 Data description

Tourist data for the UK is the inbound tourist number, which is the number of overseas residents visiting the UK in thousands. The purpose of their visits is consisting of holidays, business, visiting friends or relatives etc. The source of this data is the International Passenger Survey (IPS) from the Office for National Statistics (ONS), UK. Although there is data available for the time period of 1980 to 2014, only data from 1990 to 2014 is considered to match the length of GHG emission time series. In the UK data for GHG emission estimation for the year 2014 are provisional. The definition of other greenhouse gasses is provided in the literature review section. From 1990 to 2014 there are 25 yearly observations. The emission and tourist number are written as following variables in the analysis.

1. Energy Supply
2. Business
3. Transport
4. Public
5. Residential
6. Agriculture
7. Industrial Processes
8. Waste Management
9. LULUCF (Land use, land-use change, and forestry)
10. Total Emission
11. Tourist

Because VAR/VEC model does not require a priori assumption all these equations are two way where one equation put Tourist as independent variables (exogenous) and in another dependent (endogenous) with each of the emission variables. In each of the tests, the variables for different sources of emissions are written as Agriculture for simplicity. The variable Total Emission is the algebraic sum of emissions from all the sectors and Tourist is the estimation of inbound tourist number.

4.1.1.2 Unit Root Test

As discussed in the methodology section to create the VAR or VEC model it is necessary to determine in which order the variables are stationary. Below is the unit-root test results for each of the variables. Here ADF(Augmented Dicky Fuller test) has been used to determine unit root as a test for stationarity. The value in parenthesis is the p value and without the parenthesis is the t statistics. Throughout all the statistical tests * implies 10% allowance, ** is 5% and *** is 1%.

	level	1st difference	2nd difference
Energy Supply	(0.9401) -0.08854	(0.0029)-0.0029***	
Business	(0.9916) 0.796717	(0.0000)-6.7120***	
Transport	(0.4663) -1.600	(0.0179)-3.4874**	
Public	(0.9014) -0.3562	(0.0000)-6.6060***	
Residential	(0.9965) 1.1348	(0.0000)-6.7706***	
Agriculture	(0.8526) -0.6025	(0.0003)-5.3064***	
Industrial Processes	(0.5298) -1.4727	(0.0013)-4.638***	
Waste Management	(0.6356) -1.2490	(0.0002)-5.524***	
LULUCF	(0.9994) 1.7617	(0.0377)-3.137330**	(0.0013)-4.7671***
Tourist	(0.7320) -0.9978	(0.0081)-3.9615***	
Total Emission	(0.9993) 1.704	(0.0000)-6.5338***	

TABLE 4.1: Unit root test UK (p-values <= 0.10 , 0.05 and 0.01 are marked as *,** and ***)

Here for yearly data of UK, a maximum lag length of 5 using Schwartz information criterion has been used for the ADF unit root test. As can be seen from the table, all of the variables are non-stationary in the level but stationary in the first difference. It can be seen from the table that by allowing up to 5% significance there is not enough evidence for the all the variables to have unit-root which implies they are stationary on the first difference.

4.1.1.3 Cointergation Test

Now the cointegration test is being applied as all the variables are stationary in the same order. If any of the emission variables is integrated with Tourist then the VEC model is applied without any restriction in the level. To test for cointegration, the Engle-Granger cointegration test has been applied.

	tau stat(Tourist dependent)	z stat(Tourist dependent)	tau stat(Tourist independent)	z stat(Tourist independent)
Energy Supply	-1.4806(0.7716)	-3.863(0.8076)	-0.9893(0.9047)	-4.3908(0.7617)
Business	-2.989(0.1509)	-13.4474(0.1134)	-1.398(0.8009)	-4.157(0.7825)
Transport	-1.332(0.8225)	-3.344(0.8489)	-0.5562(0.9595)	-1.3034(0.9603)
Public	-2.695(0.2351)	-9.468(0.3163)	-2.3817(0.3575)	-9.4826(0.3153)
Residential	-2.911(0.1694)	-8.471(0.3905)	-0.7558(0.9393)	-2.265845(0.9193)
Agriculture	-3.3429*(0.0825)	-21.72996***(0.0061)	-2.8437(0.1896)	-17.6616**(0.0296)
Industrial Processes	-3.1690(0.1119)	-14.4360*(0.0849)	-1.949(0.5630)	-6.7885(0.5360)
Waste Management	-5.21871*** (0.0024)	16.30012(1.0000)	-2.405794(0.3471)	-9.505048(0.2919)
LULUCF	-3.778055** (0.0376)	-38.59433*** (0.0000)	-2.609416(0.2667)	-12.75256(0.1378)
Total Emission	-3.385128*(0.0780)	-40.96513*** (0.0000)	-0.9473(0.9119)	-3.107358(0.8666)

TABLE 4.2: Cointergation test uk (p-values <= 0.10 , 0.05 and 0.01 are marked as *,** and ***)

It can be seen from the cointegration test results that Agriculture, LULUCF , and Total emission are cointegrated with Tourist with less than 1% significance. Due to this, instead of VAR, VEC is chosen for Agriculture, LULUCF, and total emission.

4.1.1.4 Lag Selection

Lag selection is an important issue in VAR or VEC models. There are two ways to select appropriate lag order. One is to test using information criteria like AIC, SC described more detailed in the methodology section and another one is keep increasing the lag order until the autocorrelation in the residuals is removed. Here first with maximum lag order 2 is selected for this lag selection tests. The reason behind this is that these are yearly data and it is being assumed that each of the variables depends on the value of only the past two years.

	AIC	SC	HQ
Energy Supply	(lag-0)-5.761640	(lag-0)-5.662454	(lag-0)-5.738275
Business	(lag-1)-6.35402	(lag-0)-6.083255	(lag-1)-6.284406
Transport	(lag-0)-8.344758	(lag-0)-8.245573	(lag-0)-8.321393
Public	(lag-1)-5.299870	(lag-0)-5.122021	(lag-1)-5.229775
Residential	(lag-1)-5.146267	(lag-1)-4.848710	(lag-1)-5.076172
Agriculture	(lag-1)-6.519622	(lag-0)-6.330280	(lag-1)-6.449526
Industrial Processes	(lag-0)-4.643101	(lag-0)-4.543916	(lag-0)-4.619736
Waste Management	(lag-2)-4.321690	(lag-0)-4.133451	(lag-0)-4.209271
LULUCF	(lag-1)-4.794726	(lag-1)-4.497169	(lag-1)-4.724630
Total Emission	(lag-1)-6.955329	(lag-0)-6.761962	(lag-1)-6.885234

Table 4.3: Lag selection UK

The test result shows that all the criteria for some of the variables have all zero lag order. In order to test for VAR Granger non-causality, at least one lag needs to be included.

4.1.1.5 Auto-correlation Test for UK

Here two methods are used to test for residual autocorrelation. One is portmanteau autocorrelation test and another one is the BreuschGodfrey serial correlation Lagrange multiplier test (LM) test. The test is done from lag order 1 and estimates a VAR(or VEC for cointegrated variables) the lag order is increased until there is enough evidence to believe that there exists no auto-correlation. Here the test for higher order lags up to 17 is considered to test for auto-correlation. The already included lag orders in the model are invalid for the portmanteau autocorrelation test. If there is evidence that 50% or less amount of lags are not autocorrelated than the model is considered for Granger non-causality test in the next step.

	lag	Portmanteau Test for Autocorrelation upto -17	LM test for autocorrelation upto -17
Energy Supply	1(var)	no autocorrelation to any of the lags	only lag 8 shows autocorrelation for 10% allowance
Business	1(var)	no autocorrelation	only lag 8 shows autocorrelation for 10% allowance
Transport	1(var)	no autocorrelation	no autocorrelation
Public	1(var)	adjusted Q-stat shows evidence for autocorrelation from lag-4	lag 1,6,10 shows evidence for autocorrelation
	2(var)	adjusted Q-stat shows auto-correlation from 3, 5-15	lag 6,10 shows autocorrelation
	3(var)	no autocorrelation from lag 5(1,2,3 included as lag)	lag 6,14,15 shows autocorrelation
Residential	1(var)	no autocorrelation	lag 4,15,16 shows evidence for autocorrelation
Agriculture	1(vec)	no autocorrelation	no autocorrelation
Industrial Processes	1(var)	no autocorrelation	lag 8,14 shows evidence for autocorrelation
Waste Management	1(var)	autocorrelation: 2, 4-13	autocorrelation lag: 1,2,5
	2(var)	autocorrelation 5-8,10	no autocorrelation
LULUCF	1(vec)	no autocorrelation	no autocorrelation
Total Emission	1(vec)	no autocorrelation	autocorrelation 5,13

TABLE 4.4: Autocorrelation test

4.1.1.6 Causality Test for UK

Now the Wald test is performed for Granger non-causality test.

	method	Tourist dependent: chi-sqr(probability)	emission dependent:chi-sqr (probability)
Energy Supply	1(var)	0.118931(0.7302)	0.000915(0.9759)
Business	1(var)	1.401893(0.2364)	2.895726*(0.0888)
Transport	1(var)	0.217040(0.6413)	1.791977(0.1807)
Public	3(var)	0.7129(1.368793)	0.1691(5.037712)
Residential	1(var)	0.456725(0.7992)	0.359415(0.5488)
Agriculture	1(vec)	9.329331***(0.0023)	0.099137(0.7529)
Industrial Processes	1(var)	0.466169(0.4948)	2.631693(0.1047)
Waste Management	2(var)	1.337363(0.5124)	12.27287***(0.0022)
LULUCF	1(vec)	0.532560(0.4655)	1.106878(0.2928)
Total Emission	1(vec)	1.956308(0.1619)	1.629054(0.2018)

Table 4.5: UK Granger causality (p-values <= 0.10 , 0.05 and 0.01 are marked as *,** and ***)

The following evidence of causality where tourism might be Granger causing emissions are detected:

1. Tourist seems to be causing emissions from Waste Management (rejecting the null of non-causality because P value is less than 1%).
2. Tourist seems to be causing emission from Business (rejecting the null of non-causality because P value is less than 10%).

Also, the following reverse causality from emission to tourism seems to exist:

1. Emission from Agriculture seems to be causing Tourist (rejecting null of non-causality because P value is less than 1%)

4.1.2 Granger non-causality test results for Australia

4.1.2.1 Data description

The Granger causality test for Australia is done by analysing time series data for inbound tourist numbers and different sectors of emission. These time series data are quarterly, ranging from 2004 third quarter, march-2005 to the first quarter of 2014 which is September-2014. In total, there are 39 data points. The time series are seasonally unadjusted and emissions are sector wise divided into 8 sectors including two totals. One of the totals is the sum of all other emissions except LULUCF and another one includes LULUCF. Followings are the time series variables considered for time series analysis considered in this study:

1. Electricity
2. Stationary Energy (excluding electricity)
3. Fugitive Emissions
4. Industrial Processes and Product Use
5. Agriculture
6. Waste Management
7. Land Use, Land Use Change and Forestry (LULUCF)
8. Tourist
9. Transport
10. Total excluding LULUCF
11. Total including LULUCF

The Tourism Research for Australia does not provide data until March 2005 due to the incompatibility of the methodology regarding estimation method. Although more data points available for greenhouse gas emission this study only considers data from March quarter-2005 to synchronize with the available tourism data. The The data source for greenhouse gas is the Australian National Greenhouse Accounts, published by the Department of the Environment, 2014. The source of tourist numbers data is "Tourism Research Australia" and the data is provided on request.

Granger causality could conclude false positive causal relation if there exist strong seasonal effects in the series (Granger, 1976). In the Granger causal analysis for Australia, the tests are performed twice once on the raw data and again after adjusting for seasonality if detected. The Census X-13 routine has been used to remove seasonal effects (U.S. Census Bureau, 2015). Census X-13 is a tool for seasonal adjustment, developed and maintained by United State's Census Bureau.

4.1.2.2 Unit root test on unadjusted data

The following table shows unit root result using augmented Dicky fuller test using Schwartz info criterion by selecting maximum lag 4.

	level	first diff	second
Agriculture	0.2828	0.3866	0.0000***
electricity	0.8592	0.0000***	0.0000***
Fugitive Emissions	0.5728	0.0000***	0.0000***
Industrial Processes and Product Use	0.0065		
Land Use, Land Use Change and Forestry (LULUCF)	0.6538	0.0000***	0.0000***
Stationary Energy (excluding electricity)	0.9019	0.0129**	0.0000***
Total excluding LULUCF	0.0002	0.0000***	
Total including LULUCF	0.8575	0.0000***	0.0000***
Tourist	1.0000	0.0973*	0.0000***
Transport	0.1914	0.0171**	0.0000***
Waste	0.9148	0.0000***	0.0000***

TABLE 4.6: Stationarity test for different sectors Australia using Schwartz information criterion on unadjusted time series (p-values <= 0.10 , 0.05 and 0.01 are marked as *,** and ***)

If the null is rejected if p-values are <= 0.05, it can be seen from the ADF test result that most of the series contains unit root in the level except Industrial Processes and Product Use and Total excluding LULUCF. Even after the 1st difference Tourist and Agriculture seem to have unit-root. In the 2nd difference, it appears that no series contain unit-root. Although most of the series are stationary in 1st difference only second differenced series will be used to estimate the models because all the models will have Tourist series and the time series variable Tourist is only stationary in 2nd difference. All these tests have been done without considering a linear trend in the data.

4.1.2.3 Cointergration, Auto-correlation and Causality Test on Unadjusted Data

dependent variables (one to many with with Tourist)	cointegration	lag	auto-correlation(12 lag,0.05)	Granger Causality
Agriculture	EG-NO,JS-NO	LR-3,AIC-7,SC-3	PM-Yes(7),LM-No(11)	NO
electricity	diff order	LR-3, AIC-8, SC-3	PM-YRD(6),LM-NO(11)	NO
Fugitive Emissions	diff order	LR-7,AIC-9,SC-4	PM-yes(4),LM-NO(11)	NO
Industrial Processes and Product Use	diff order	LR,SC-4,AIC-9	LM-NO(ALL),PM-yes(ALL)	lag-4 Tourist independent(0.0052***)
Land Use, Land Use Change and Forestry (LULUCF)	diff order	LR-3,AIC-8,SC-3	PM-YES(ALL),LM-10(NO)	NO
Stationary Energy (excluding electricity)	diff order	LR,AIC, SC-8	PM-YES(ALL),LM-10(NO)	lag9- Tourist dependent(0.0023***)
Total excluding LULUCF	diff order	SC,LR-4,AIC-9	LM-no(11),pm-yes(6)	lag4- Tourist independent(0.0215**)
Total including LULUCF	diff order	SC,LR-3,AIC-9	PM-no(7),LM-No All	lag3-Tourist independent(0.0087***)
Transport	diff order	SC,LR-3,AIC-9	PM-yes(all),LM-No (9)	lag3-Tourist independent(0.0006***), Tourist dependent(0.0321**)
Waste	diff order	LR, AIC-7,SC- 3	PM-yes(5),LM-No All	NO

Time series variables Tourist and Agriculture is tested for cointegration due to the same order stationarity. The Engle-Granger two-step method is used for cointegration tests and test results show that these two time series variable are not cointegrated. In the table, EG refers to the Engle-Granger cointegration test. Based on the ADF unit root test results the VAR model is estimated on 2nd differenced time series variables. In order to setup the var model three lag selection criteria have been used and they are Likelihood Ratio (LR), Akaike information criterion (AIC), Schwarz information criterion (SC). The lag order is selected on a majority basis of the test results from the selection criteria. Where all the lag selection criteria select different lag AIC is preferred for selecting appropriate lag for example in the case of Fugitive Emission we are using lag 9. After selecting lag order the VAR model is estimated using the Ordinary least Square method. Similar to Granger causality analysis for UK Block Exogeneity Wald Tests are used to test for Granger causality. Granger causality test results reveals the following causality:

1. Tourist is causing emission from Industrial Processes and Product Use in Australia
2. Tourist is causing emission from Transport in Australia
3. Tourist is causing emission from Total excluding LULUCF in Australia
4. Tourist is causing emission from Total including LULUCF in Australia

Interestingly there exists causal relations from emissions to tourist number as well.

1. Emission from transportation seemed to be causing Tourist.
2. Emission from Stationary Energy (Excluding electricity) seemed to be causing Tourist

4.1.2.4 Unit Root Test on Seasonally Adjusted Data

Now the same test is performed on seasonally adjusted data. In order to perform seasonal adjustment, Census-X13 is used. Census-X13 it has detected seasonality in all the time series variables except Fugitive Emissions and Stationary Energy.

	level	first diff
Agriculture	-1.894843(0.3310)	-5.397665***(0.0001)
electricity	-0.431715(0.8929)	-8.282696(0.0000)
Fugitive Emissions(no seasonality)	-5.528849***(0.0000)	
Industrial Processes and Product Use	-3.254819**(0.0248)	-4.387456***(0.0013)
Land Use, Land Use Change and Forestry (LULUCF)	-1.412288(0.5658)	-5.507743***(0.0001)
Stationary Energy (excluding electricity)(no seasonality)	0.365957(0.9785)	-10.52451***(0.0000)
Total excluding LULUCF	-3.205651**(0.0276)	-8.744146***(0.0000)
Total including LULUCF	-1.033892(0.7309)	-7.698465***(0.0000)
Tourist	0.733128(0.9913)	-7.147206***(0.0000)
Transport	-1.231781(0.6502)	-9.531728***(0.0000)
Waste	-0.128105(0.9388)	-5.328838***(0.0001)

Table 4.8: ADF unit root test Australia (p-values <= 0.10 , 0.05 and 0.01 are marked as *,** and ***)

The ADF unit root test is performed by using Schwartz info criterion for lag selection with the maximum lag order of 9. The unit test results shows= that fugitive emissions not only does not have seasonality but also it is stationary in the level and its not even possible to accept unit root by allowing 1% significance. Also, Total excluding LULUCF does not have unit root for 5% allowance in the level. Census X-13 could not detect seasonality for Stationary Energy (excluding electricity) as well.

4.1.2.5 Cointegration Test on Seasonally Adjusted Data

	tau (log(Tourist) dependent)	z (log(Tourist) dependent)	tau (log(Tourist) INdependent)	z (log(Tourist) INdependent)
Agriculture	0.542765 (0.9974)	1.006892 (0.9966)	-1.928872(0.5703)	-5.262205 (0.6923)
electricity	-3.423217* (0.0595)	-20.49792** (0.0218)	-4.004858**(0.0163)	-23.18633*** (0.0094)
Fugitive Emissions(no seasonality)	different order stationary	different order stationary	different order stationary	different order stationary
Industrial Processes and Product Use	-0.345472 (0.9739)	-0.796115 (0.9739)	-3.797358** (0.0268)	-29.70645*** (0.0009)
Land Use, Land Use Change and Forestry (LULUCF)	-1.043034 (0.8943)	-4.005404 (0.8008)	-2.053847 (0.5077)	-8.026560 (0.4520)
Stationary Energy (excluding electricity) (no seasonality)	-1.344398 (0.8183)	-9.096543 (0.3685)	-5.232444*** (0.0007)	-61.79526*** (0.0000)
Total excluding LULUCF	different order stationary	different order stationary	different order stationary	different order stationary
Total including LULUCF	-1.7717771(0.6468)	-8.338069 (0.4277)	-2.361375 (0.3587)	-10.42283 (0.2855)
Transport	-1.284899(0.8362)	-5.242799 (0.6940)	-2.084141 (0.4925)	-7.940277 (0.4590)
Waste	-3.004774(0.1354)	3162.209 (1.0000)	-1.928430 (0.5705)	-7.351263 (0.5075)

TABLE 4.9: Cointegration Test (p-values <= 0.10 , 0.05 and 0.01 are marked as *,** and ***)

The cointegration test for Australia shows that Electricity, Industrial Processes and Product Use, Stationary Energy(excluding electricity) are cointegrated with Tourist. In these cases a vector error correction(VEC) model is used instead of VAR and the reason is discussed in the methodology chapter.

4.1.2.6 Lag Selection Test on Seasonally Adjusted Data

	AIC	SC	HQ
Agriculture	-11.57550 (lag-9)	-10.22452 (lag-2)	-11.01438 (lag-9)
electricity	-10.00279 (lag-9)	-9.429560 (lag-1)	-9.623852 (lag-1)
Fugitive Emissions	-7.702677 (lag-5)	-7.181691 (lag-1)	-7.467435 (lag-2)
Industrial Processes and Product Use	-8.988839 (lag-7)	-8.366235 (lag-2)	-8.690065 (lag-2)
Land Use, Land Use Change and Forestry (LULUCF)	-3.643304 (lag-1)	-3.360416 (lag-1)	-3.554707 (lag-1)
Stationary Energy (excluding electricity)	-9.715691 (lag-9)	-8.263481 (lag-1)	-9.154575 (lag-9)
Total excluding LULUCF	-11.23024 (lag-1)	-10.94735 (lag-1)	-11.14165 (lag-1)
Total including LULUCF	-11.14866 (lag-9)	-10.54072 (lag-1)	-10.73502 (lag-1)
Transport	-11.25926 (lag-1)	-10.97637 (lag-1)	-11.17066 (lag-1)
Waste	-12.51326 (lag-9)	-10.80437 (lag-1)	-11.95215 (lag-9)

Table 4.10: Lag selection

In this test, the minimum number of lag is selected from AIC, SC, and HQ, for example in the case of Agriculture lag order 2 is used in the model. After the model is estimated using ordinary least square estimation the residuals are tested for autocorrelation. In case there is autocorrelation, more lag is included in the model until the autocorrelation is removed in higher lag orders.

4.1.2.7 Autocorrelation Test on Seasonally Adjusted Data

In the table, the lag order P is increased in the VAR(p) or VEC(p) model until the majority of higher order lag does not show autocorrelation. For example in the case of Fugitive Emissions in VAR(1) and VAR(2) using the Portmanteau autocorrelation test shows that all the higher order lags are autocorrelated so the other LM test is not being applied and the lag order is increased in the model. In a case of VAR(3) both of the test results shows that there is no autocorrelation in the higher lag orders.

	lag	Portmanteau Test for Autocorrelation upto -()	LM test for autocorrelation upto -
Agriculture	var(2)	(20)none	(20)none
electricity	vec(1)	(20)none	(20)4,12,15,19,20
Fugitive Emissions(no seasonality)	var(1)	all lag autocorrelated	
	var(2)	all lag auto correlated	
	var(3)	(20)none	(20)none
Industrial Processes and Product Use	vec(2)	(20)none	(20)none
Land Use, Land Use Change and Forestry (LULUCF)	var(1)	(20)none	12,16
Stationary Energy (excluding electricity) (no seasonality)	vec(1)	half autocorrelated	
	vec(2)	all autocorrelated	
Total excluding LULUCF	vec(3) var(1)	none none	only at lag 1 but for 10% allowence lag 4 and 19
Total including LULUCF	var(1)	none	4,11,15,16,19,20
	var(2)	20	4,11,15,16,19,20
	var(3)	4	1,10,19,20
	var(4)	none	19(10% allowance)
Transport	var(1)	7-11,13,16-20	none
	var(2)	8-11,13,16,17	15,16
	var(3)	no autocorrelation	16,19
Waste	var(1)	no autocorrelation	14,19

Table 4.11: auto-correlation test on seasonally adjusted data for Australia(see appendix A for detail)

4.1.2.8 Causality Test on Seasonally Adjusted Data

	method	Tourist dependent: chi-sqr(probability)	emission dependent: chi-sqr(probability)
Agriculture	var(2)	1.842808(0.3980)	1.287979(0.5252)
electricity	vec(1)	0.426220(0.5138)	0.730706(0.3927)
Fugitive Emissions	var(3)	1.354300(0.7163)	10.52585**(0.0146)
Industrial Processes and Product Use	vec(2)	5.397507*(0.0673)	5.499413*(0.0639)
Land Use, Land Use Change and Forestry (LULUCF)	var(1)	0.918112(0.3380)	1.649436(0.1990)
Stationary Energy (excluding electricity)	vec(3)	3.266226(0.3524)	1.414125(0.7022)
Total excluding LULUCF	var(1)	3.690894*(0.0547)	0.388773(0.5329)
Total including LULUCF	var(4)	0.481153(0.9753)	4.782883(0.3103)
Transport	var(3)	7.752703*(0.0514)	1.004768(0.8001)
Waste	var(1)	0.038457(0.8445)	0.072666(0.7875)

TABLE 4.12: Causality test on Seasonally adjusted data for Australia (p-values <= 0.10 , 0.05 and 0.01 are marked as *,** and ***)

The Block Exogeneity Wald test is performed to test for Granger non-causality. The followings the causal relations are detected:

1. Tourist seems to be causing emission from Industrial Processes and Product Use (rejecting the null of non-causality if the P value is less than 10%).
2. Tourist seems to be causing Fugitive Emission (rejecting the null of non-causality if the P value is less than 5%).

Also, the tests show causality from emission to Tourist as well.

1. Emission from Industrial Processes and Product Use seems to be causing Tourist (rejecting the null of non-causality if the P value is less than 10%).
2. Emission from total excluding LULUCF seems to be causing Tourist (rejecting the null of non-causality if the P value is less than 10%).
3. Emission from Transport seems to be causing Tourist (rejecting the null of non-causality if the P value is less than 10%).

4.2 CCM Approach

One of the main drawbacks of Convergent Cross mapping (CCM) is, it require comparatively longer time series. The usual requirement of CCM to be able to reconstruct the dynamics of the system using state space reconstruction technique is at least > 25/30 observations (Maher and Hernandez, 2015) (Sugihara et al., 2012) (Clark et al., 2015). Due to this reason in this study CCM is applied only for Australian tourism and emission data. In the UK the available time series length does not meet the minimum requirement.

4.3 CCM Causality for Australia

4.3.1 Selecting Embedding Dimension

To perform state space construction to reconstruct the shadow manifolds, each of the time series is used to perform prediction using simplex projection, a nonlinear forecasting method in order to determine the best embedding dimension. The embedding dimension is chosen by plotting each of the time series prediction power (Pearson correlation coefficient) one step future with respect to different embedding dimension.

Below are the plots to identify the best embedding dimension for inbound tourist number for Australia and for different greenhouse gas emission sectors:

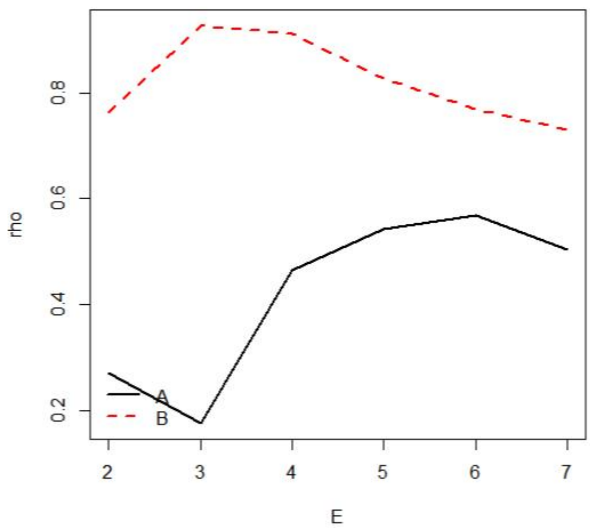

FIGURE 4.1: Embedding dimension for A=Fugitive Emissions, B = Tourist. Embedding dimension for fugitive emissions is 6. The embedding dimension E with respect to predictability rho is maximised at point 6.

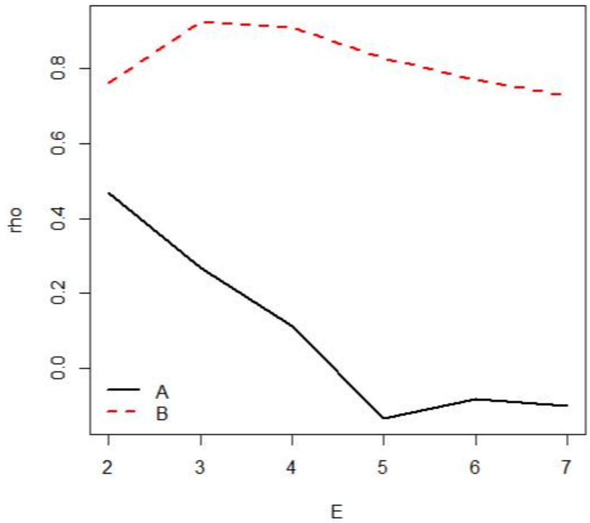

FIGURE 4.2: Embedding dimension for A=Industrial Processes and Product Use, B = Tourist . Embedding dimension for A is 2. The embedding dimension E with respect to predictability rho is maximised at point 2.

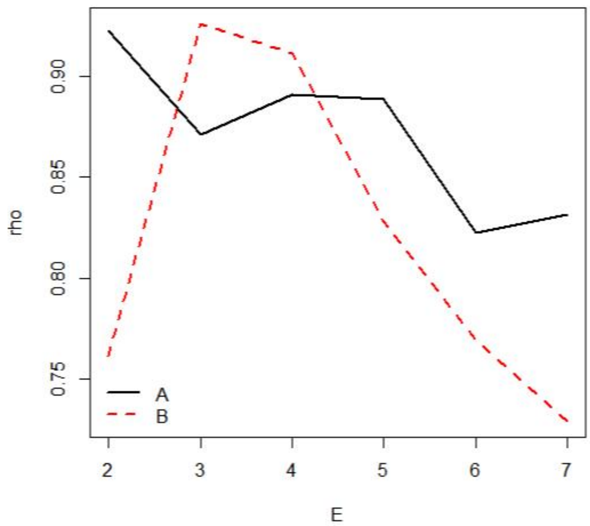

FIGURE 4.3: Embedding dimension for A=LULUCF, B = Tourist. Embedding dimension for LULUCF is 2. The embedding dimension E with respect to predictability rho is maximised at point 2.

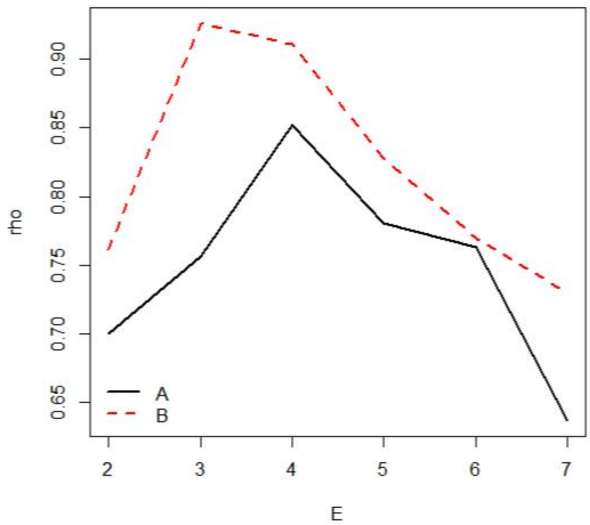

Figure 4.4: Embedding dimension for A=Stationary Energy excluding electricity, B = Tourist. Embedding dimension for A is 4. The embedding dimension E with respect to predictability rho is maximised at point 4.

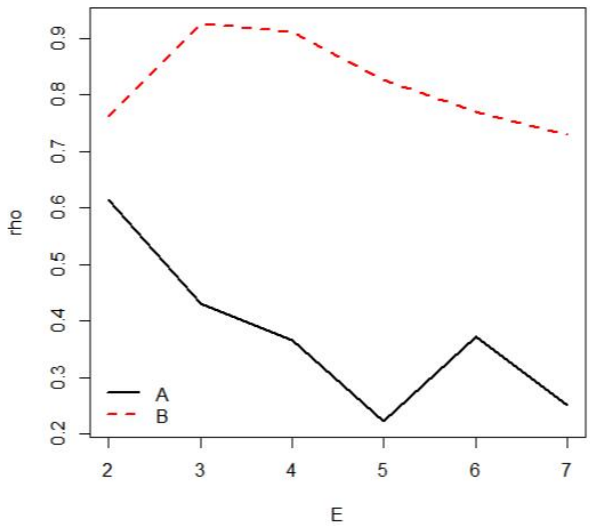

Figure 4.5: Embedding dimension for A=Totalexcluding LULUCF, B= Tourist. Embedding dimension for A is 2. The embedding dimension E with respect to predictability rho is maximised at point 2.

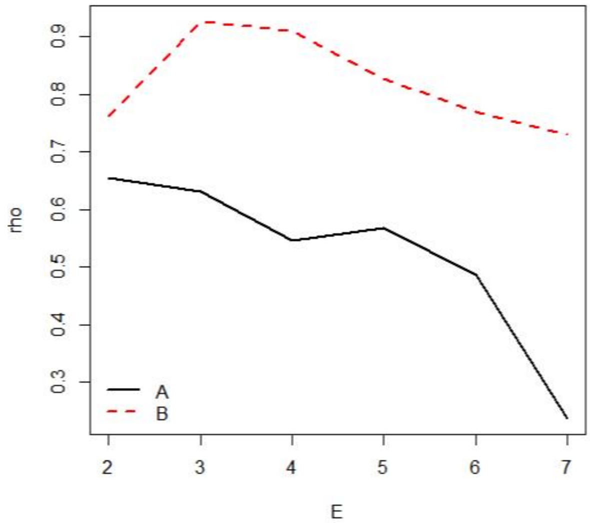

Figure 4.6: Embedding dimension for A=agriculture, B = Tourist. Embedding dimension for agriculture is 2. The embedding dimension E with respect to predictability rho is maximised at point 2.

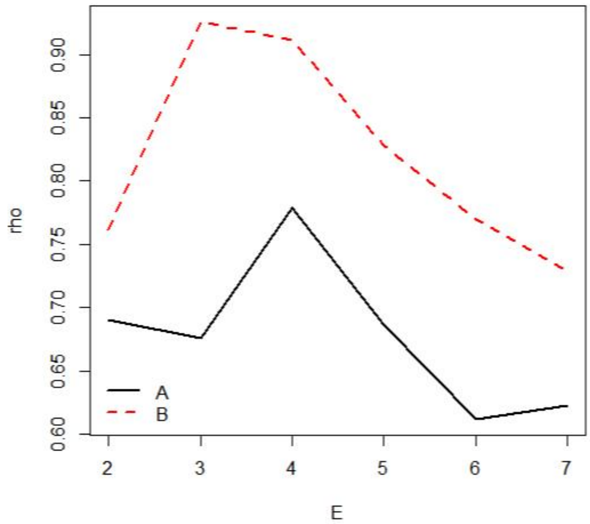

Figure 4.7: Embedding dimension for A=electricity, B = Tourist. Embedding dimension for electricity is 4. The embedding dimension E with respect to predictability rho is maximised at point 4.

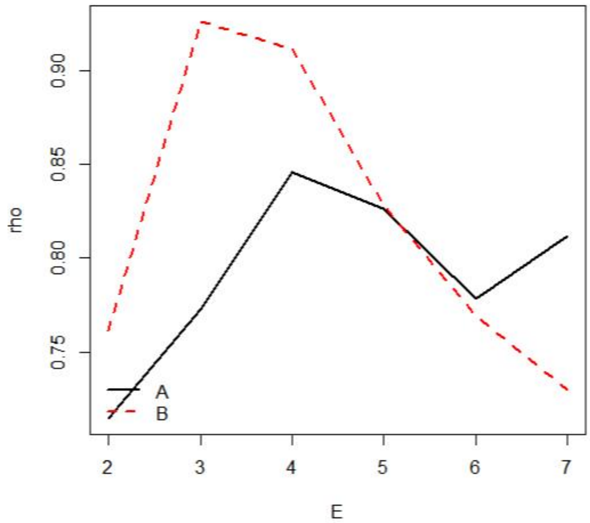

FIGURE 4.8: Embedding dimension for A=Total includingLULUCF, B=Tourist . Embedding dimension for A is 4. The embedding dimension E with respect to predictability rho is maximised at point 4.

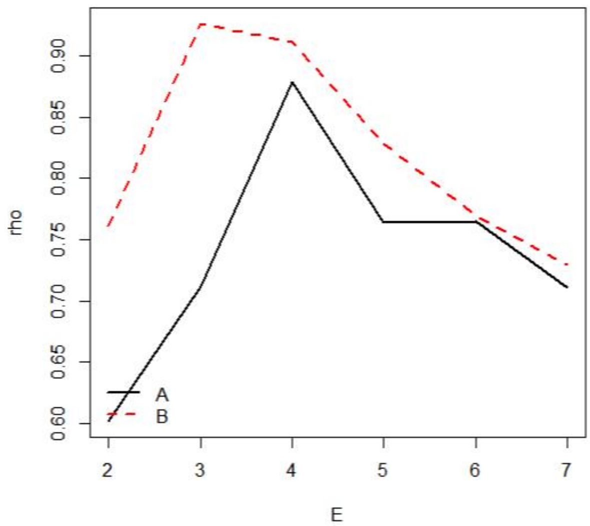

FIGURE 4.9: Embedding dimension for A=transport, B = Tourist . Embedding dimension for fugitive emissions is 6. The embedding dimension E with respect to predictability rho is maximised at point 6.

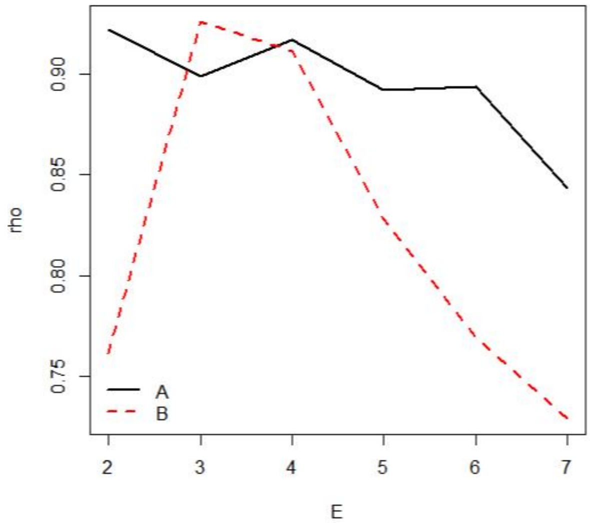

FIGURE 4.10: Embedding dimension for A=waste, B = Tourist. Embedding dimension for transport is 4. The embedding dimension E with respect to predictability rho is maximised at point 4.

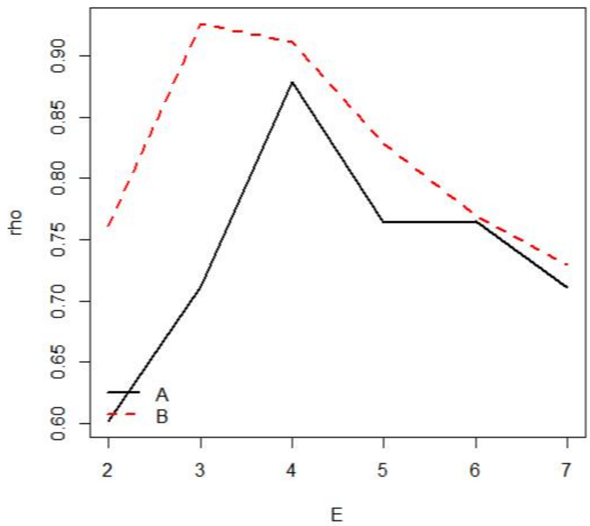

FIGURE 4.11: Embedding dimension for A=transport, B = Tourist . Embedding dimension for fugitive emissions is 4. The embedding dimension E with respect to predictability rho is maximised at point 6.

4.3.2 Nonlinearity Test Using Simplex Projection

In order to test for causality, it is necessary to determine if the time series is nonlinear deterministic, as CCM works best when the system is nonlinear. The prediction is done by plotting prediction skill (vertical axis) with respect to prediction skill for future data. In the vertical axis, each point refers to prediction steps. In cases of nonlinearity it is expected that the prediction skill should be reduced as step size is increased.

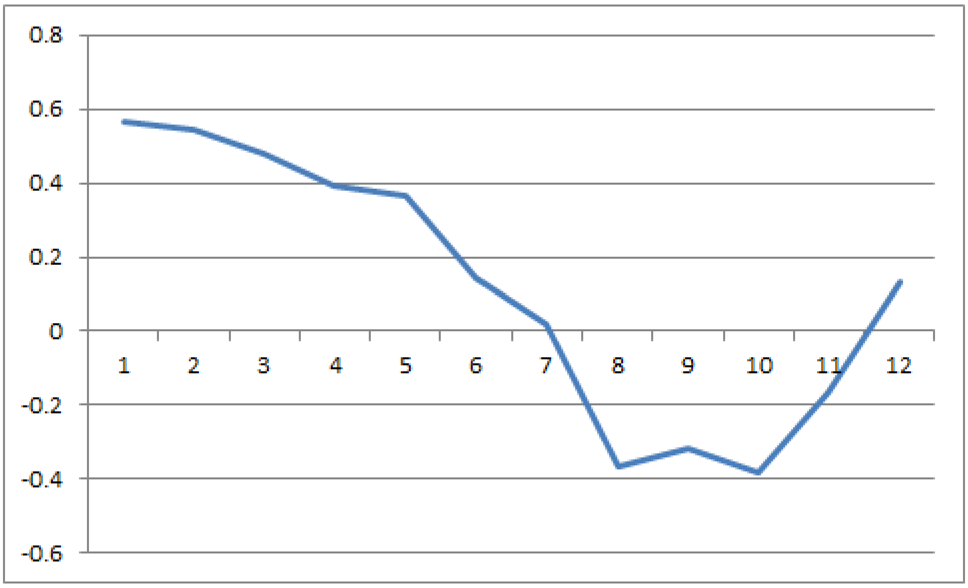

FIGURE 4.12: non-linearity test for fugitive emissions

From the above figure, it can be seen that prediction skill is reduced and then increased as a result there is not enough evidence of nonlinearity in the system for fugitive emission.

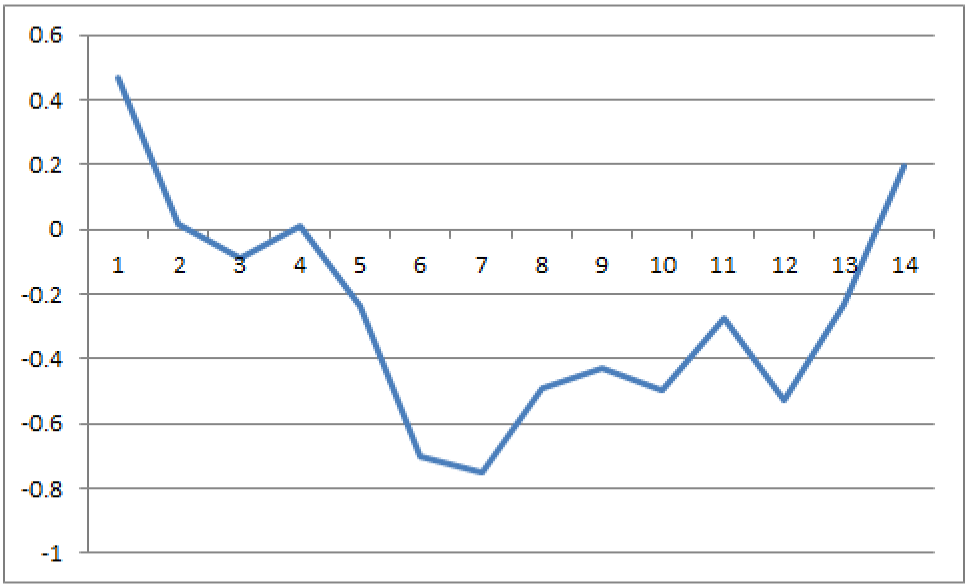

FIGURE 4.13: non-linearity test for industrial processes and product use.

In the case of GHG emission from Industrial Processes and Production Use the prediction skill with respect to step size in time is U-shaped which could be due the reason that there is a periodicity in the system (Clark et al., 2015). As a result, there is no evidence of nonlinearity using the simplex projection method.

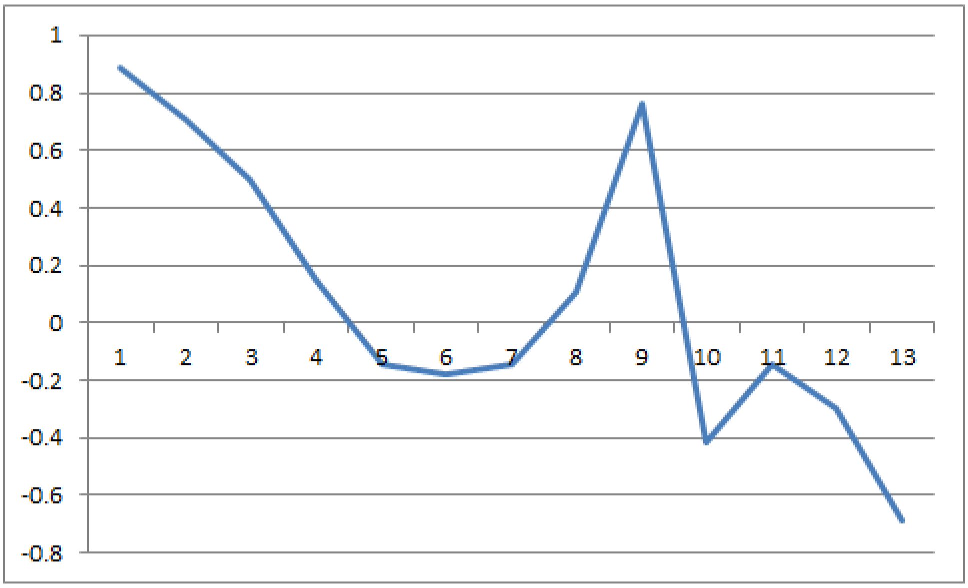

FIGURE 4.14: non-linearity test for LULUCF

In this case of LULUCF, the prediction strength is reduced and then there are spikes. It is felt that these could be due to noise and cyclic components in the data and thus nonlinearity is not concluded (Clark et al., 2015).

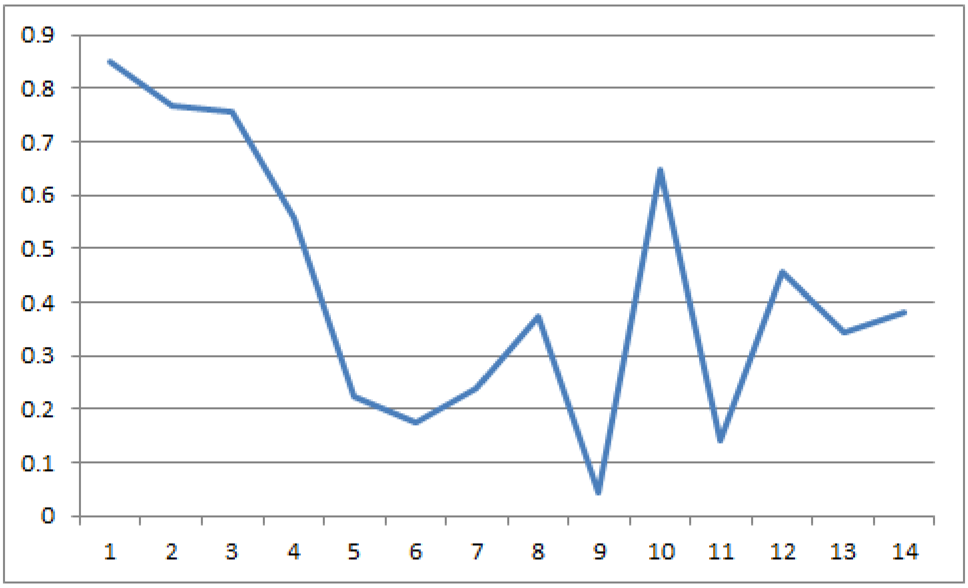

FIGURE 4.15: non-linearity test for stationary energy excluding electricity

The graph for stationary energy excluding electricity shows spikes in prediction strength with respect to step interval. The graph is indicative of detection failure of nonlinearity.

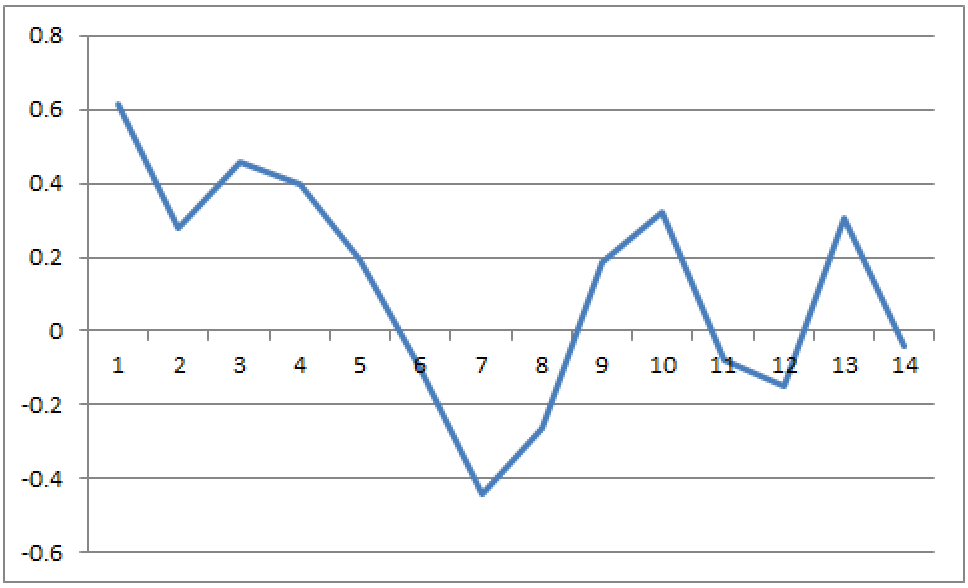

Figure 4.16: non-linearity test for total excluding LULUCF

Non-linearity test for total excluding LULUCF shows spikes in prediction strength with respect to step interval which is conclusive of failure to detect non-linearity in the system.

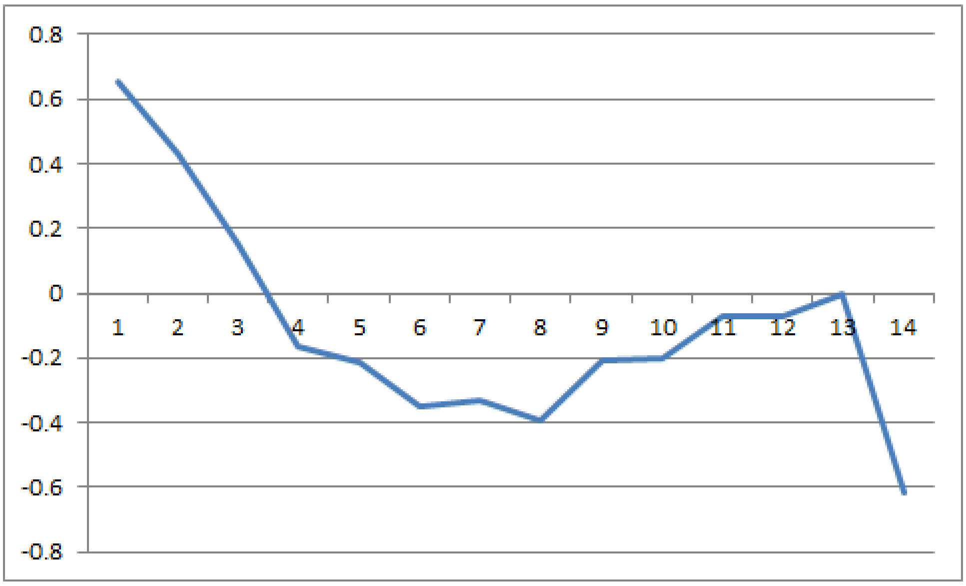

Figure 4.17: non-linearity test for agriculture

Agriculture shows that prediction strength is reduced with respect to prediction interval which may refer to nonlinearity in the system.

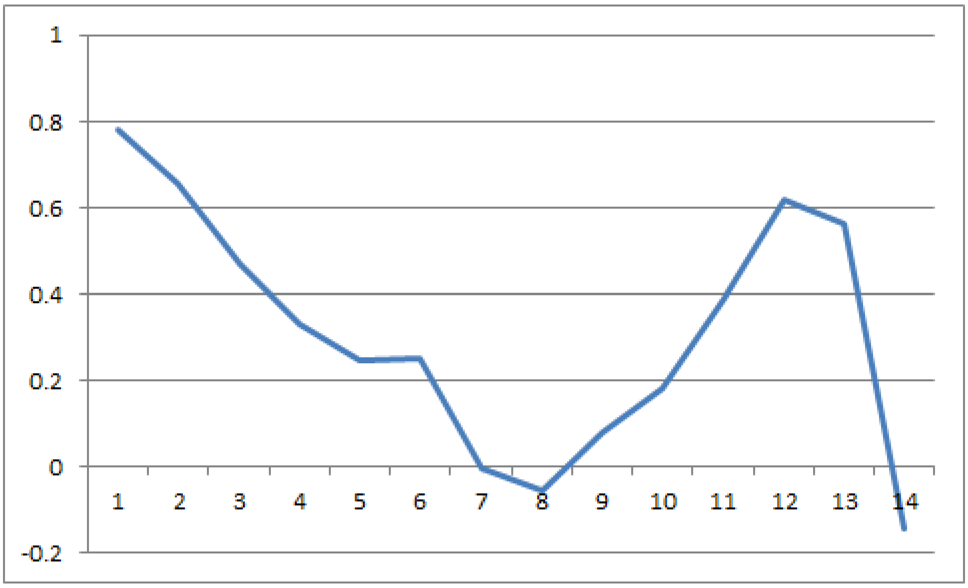

Figure 4.18: non-linearity test for electricity

Nonlinearity tests for electricity show that prediction skill is reduced and then hugely increased, before reducing again, this refers to stochastic behaviour in the system.

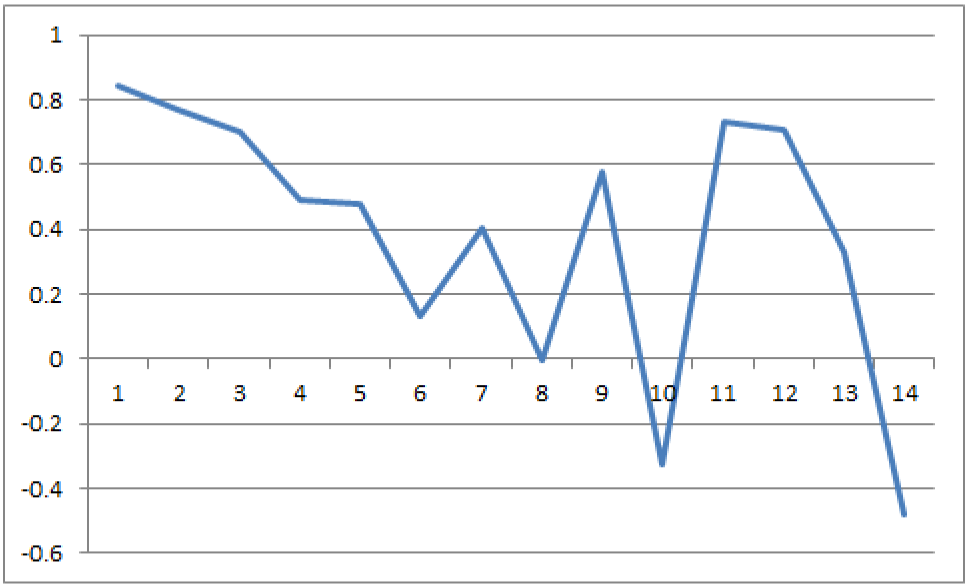

Figure 4.19: non-linearity test for total including LULUCF

The Nonlinearity test for Total Including LULUCF shows spikes, as a result nonlinearity is inconclusive.

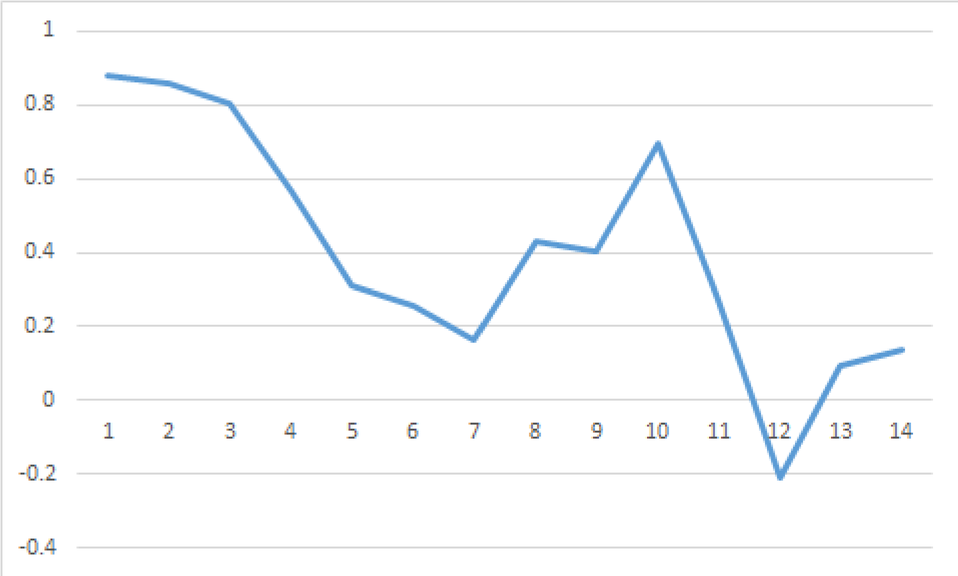

FIGURE 4.20: non-linearity test for transport

The nonlinearity test for Transport does not show a reduction of prediction strength with respect to step interval which provides no evidence for nonlinearity.

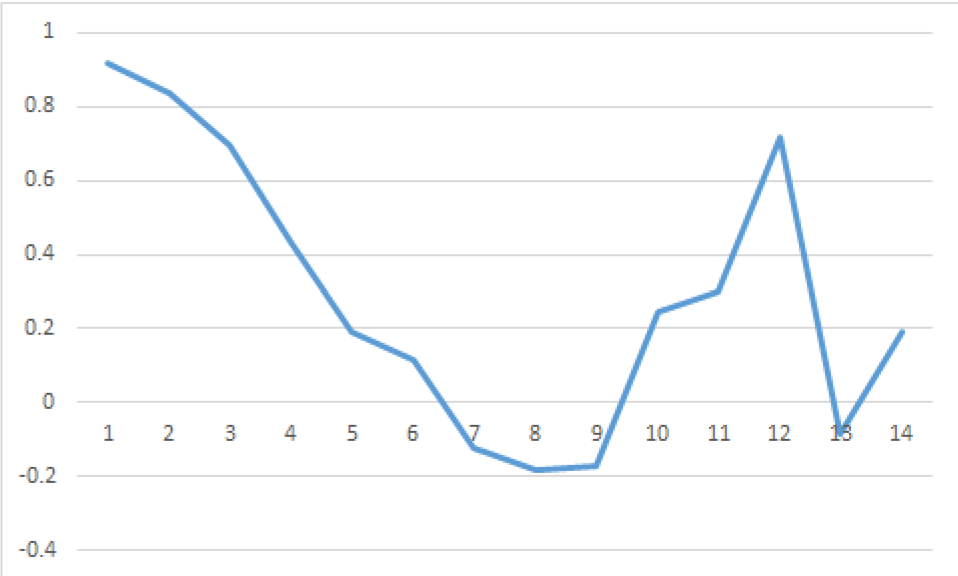

FIGURE 4.21: non-linearity test for waste

Nonlinearity is not concluded from the time-step vs prediction strength graph because the prediction is not gradually decreased.

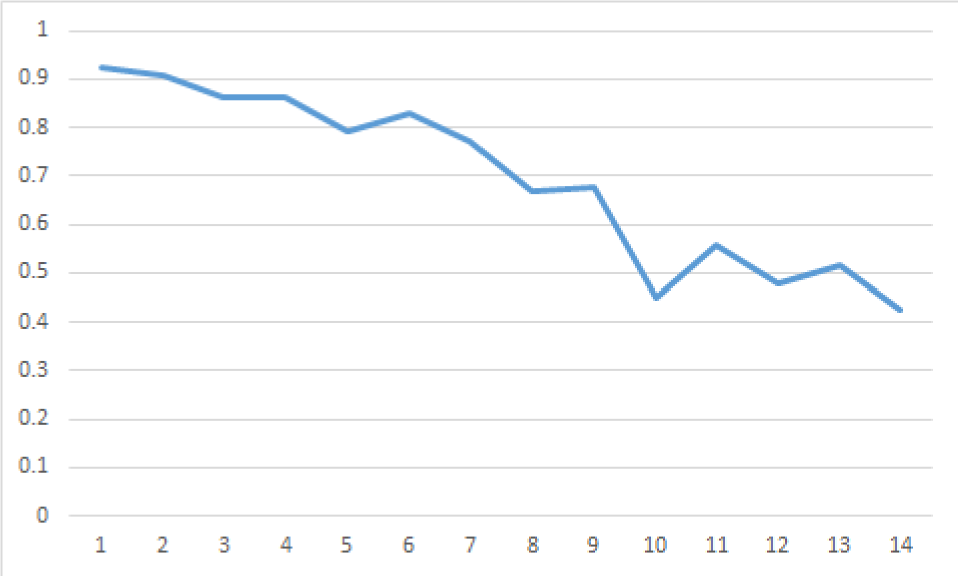

FIGURE 4.22: non-linearity test for Tourist

Nonlinearity test using simplex projection technique shows that prediction strength is declining with step interval which is indicative of nonlinearity present in the system. This supports the analysis done by Burger et al. (2001) that perhaps forecasting for Tourist is better done with nonlinear techniques such as artificial neural networks.

4.3.3 CCM test Results

Using simplex projection, nonlinearity is detected in emissions from agriculture and tourist numbers. Due to this CCM is only applied for analysing causal relations between agriculture and tourists numbers. To perform the analysis open source library CauseMap has been used. This is an implementation of CCM, written in programming language Julia. (Maher and Hernandez, 2015).

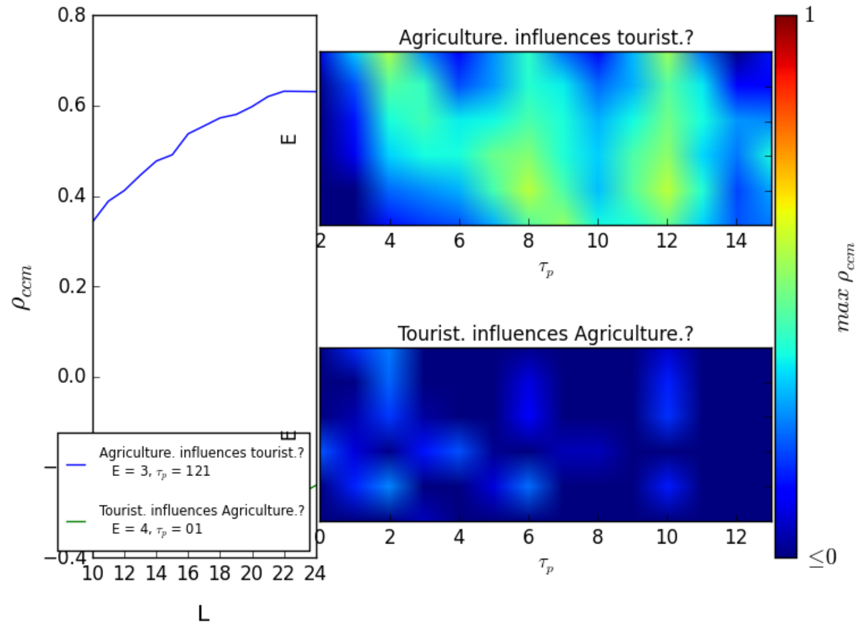

FIGURE 4.23: ccm test result for agriculture

It can be seen that Tourist causing emissions from Agriculture has little or no evidence. The heat map shows Tourist influences Agriculture shows no significant causal relation in terms of predictability. Which implies that the reconstructed manifold of Agriculture does not hold enough information to predict Tourist for increasing time series data. The prediction is done for out-of-sample data. On the other hand, it can be seen that emission from agriculture is somehow influencing Tourist because there is a significance rise in the predictability. This implies time series Tourist holds enough information which could be used to predict emission from Agriculture. The causality in CCM is concluded if the caused variable has enough information to predict the effect.

4.4 CCM Causality for 21 EU Countries

Using Spatial CCM, 21 EU countries have been analysed for Tourist-Emission relation. The method used in the analysis is called spatialCCM which has been discussed in details in the methodology chapter.

EU Countries included:

1. Austria
2. Belgium
3. Bulgaria
4. Cyprus
5. Denmark
6. Finland
7. France
8. Greece
9. Hungary
10. Ireland
11. Italy
12. Luxembourg
13. Malta
14. Netherlands
15. Poland
16. Portugal
17. Romania
18. Spain
19. Sweden
20. United Kingdom

The emissions considered here are measured as carbon dioxide emissions in metric tons per capita. The carbon dioxide emission stems from the burning of fossil fuels and the manufacture of cement. It includes carbon dioxide produced during the consumption of solid, liquid, and gas fuels and gas flaring. The data source for emissions is from World Bank's world development indicator database (The World Bank, 2015). Tourism data is collected from the World Travel and Tourism Council(WTTC) (World Travel & Tourism Council, 2015). Tourism is measured by considering visitor exports (foreign spending) [1].

4.4.1 Selecting Embedding Dimension

As it has been required for CCM tests, the best embedding dimension needs to be selected here for multispatialCCM we also have to select the best embedding dimension

[1] visitor exports are spending within the country by international tourists for both business and leisure trips, including spending on transport , but excluding international spending on education . Same kind of matrix is also used by Lee and Brahmasrene (2013) in their panel data analysis of EU countries to investigate causal relation between tourism and emission.

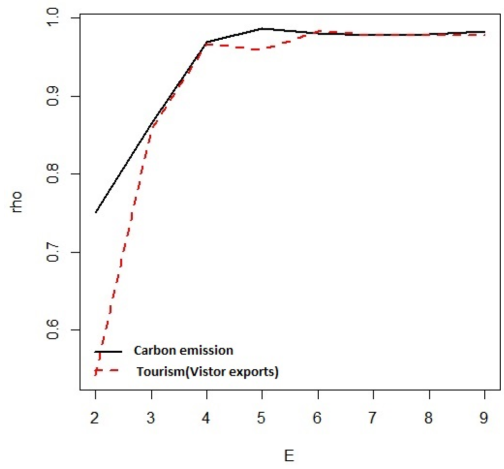

FIGURE 4.24: Best embedding dimension selection for EU countries

by plotting forecasting strength(rho) with respect to different embedding dimensions, E.

4.4.1.1 Nonlinearity Test

Before applying the multispatialCCM for causal detection the data needs to be tested for nonlinearity. Tt test the existence of desirable nonlinearity is done by using nonlinear forecasting technique simplex projection as discussed in the methodology section. MultispatialCCM has been applied using an open source R package called multispatialCCM (Clark, 2015). To test for nonlinearity the function SSR_check_signal has been used within the same package.

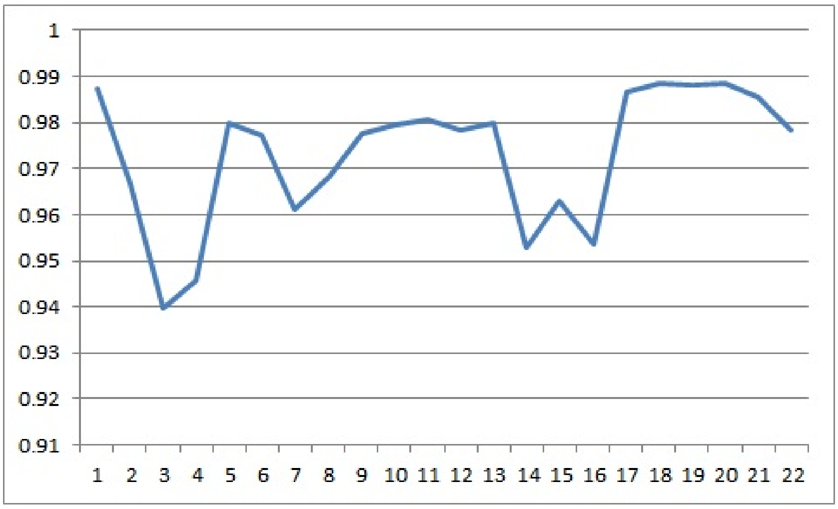

FIGURE 4.25: nonliniarity test for EU carbon emission

In the test for nonlinearity in Carbon emissions, we cannot conclude nonlinearity although prediction of *rho* is very high. The graph prediction strength on the vertical axis and step-interval on the horizontal axis shows that there is a spike in the prediction strength with a very high predictability of more than 0.93 in most of the cases.

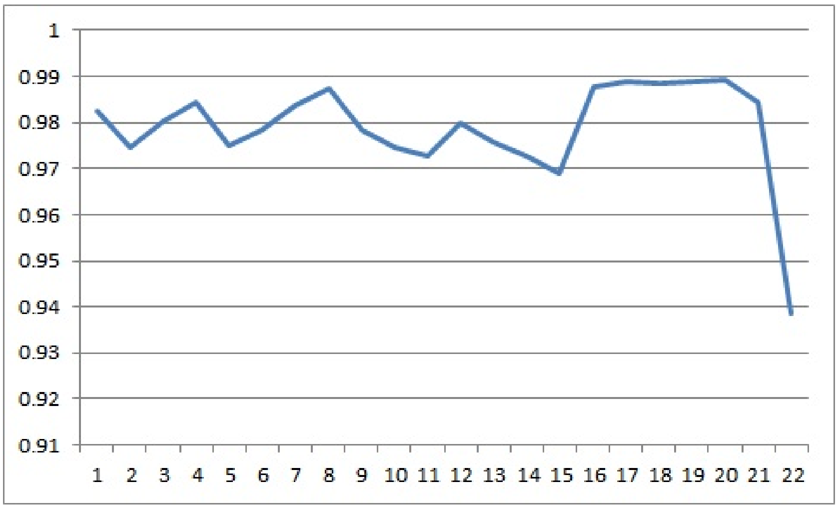

FIGURE 4.26: nonliniarity test for EU Tourist(visitor exports)

The prediction strength vs step-interval graph shows that the predictability indeed falls down which implies that there might be nonlinearity in the system. This result supports that the touristic variables are nonlinear like Burger et al. (2001) has discussed. Nonlinearity in the Tourist has also been found in the case of Australia.

4.4.1.2 Multispatial Causality Test

Below are the test results of CCM by using multispatial CCM:

As we can see the causality direction is converging with increasing library size. Also , the rho value is very high, indicating high cross-correlation. This might imply that there is a causal relation between tourism and carbon emissions for EU countries but this result cannot be considered as robust as the nonlinearity has not been detected in the case of carbon emissions for EU countries.

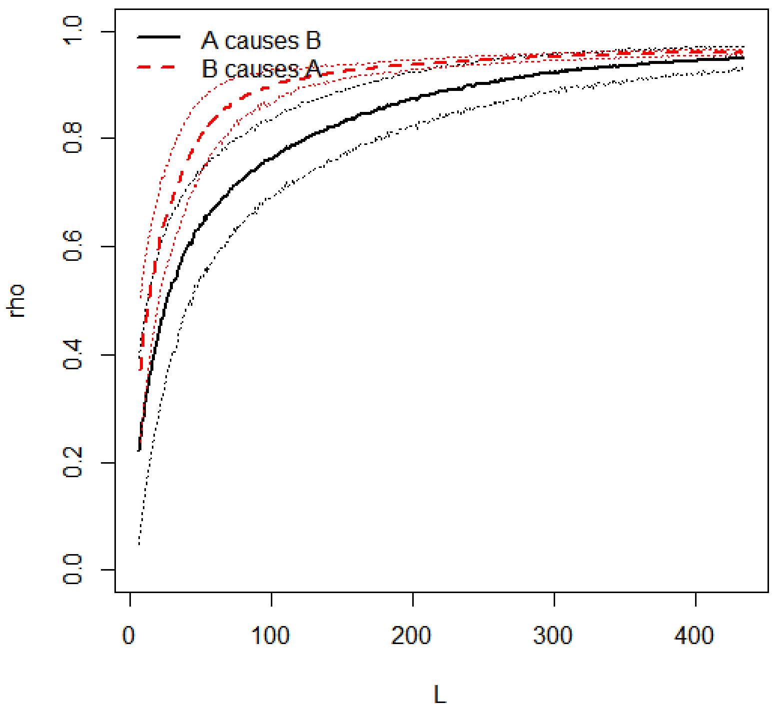

FIGURE 4.27: Test result for CCM causality test on 20 EU countries (A=Carbon,B=Visitor Export) for 1000 iteration

Chapter 5

Discussion

5.1 Granger Causality Results Analysis for UK

Tourists in the UK might be causing emissions from Waste Management. The test shows a very low p-value which is less than 1%, so there is enough statistical evidence for rejecting the null of Granger non-causal relation and accepting the alternative of a Granger causal relation. The relation between waste management and tourism is not unknown to the tourism scientist, for instance, a case study of Menorca Island (Spain) Mateu-Sbert et al. (2013) concluded that a 1% increase in tourist population causes an overall 0.282% increase in Municipal solid waste (MSW). On the other hand, one resident who is not a tourist contributes 13.2% less in MSW waste quantity when compared with a tourist. A resident seperates their waste (recyclable and non-recyclable) on average 47.3% more than a tourist. Although the environmental impact of solid waste is one of the key issues in hospitality management, Pirani and Arafat (2014) indicated that there is a substantial research gap in this particular area of sustainable solid waste management for the hospitality sector. Thus this result of tourism causing emission from waste management in the UK contributes to the increase in overall emissions from waste management for the UK. Inbound tourists to the UK might also be causing emissions from the business sectors but the result is not reliable. This is only evidenced by using p-values < 0.10 to reject the null of Granger non-causality, which is very weak evidence. Nevertheless, for the UK emissions from business have been estimated from the sub-sectors consisting of industrial combustion, refrigeration, and air conditioning. This causal relation of tourism causing emission from Business could be due to the increase in the consumptions of facilities in the hotel and overall tourist destination and facilities. This increase in the use of facilities could be contributing far more GHG emission than has been captured in the emissions data from the business sector leading to a weak

Granger causality detection. The increase in the usage of facilities which contribute to emissions from the business sector could be explained by the case study in Taiwan, where it has been showed how tourists increase the usage of air conditioning in the hotels (Tsai et al., 2014)(Huang et al., 2015).

Interestingly, there is also a causal relation from tourism to emission. In the UK, emissions from Agriculture seem to be causing tourist numbers to change. The p-value, in this case, is very low < 0.01 for accepting of the null of Granger non-causality. There is causality from climate factors to tourism as Sajjad et al. (2014) concluded that "unidirectional causality running toward climatic factors to tourism indicators" (Sajjad et al., 2014, p.12416). In Sajjad et al. (2014)'s study the causality analysis has been applied to South Asia, the Middle East and North Africa, sub-Saharan Africa, and East Asia and the Pacific regions although rather than using tourist numbers the international tourism receipt, international tourism expenditures, natural resource depletion and net forest depletion has been used as touristic variables. Emissions from Agriculture has been estimated from the sub-sectors of enteric fermentation, manure management, and miscellaneous combustion. A strong reason for this causal relation could also be due to hidden variables which might be affecting both tourism and emissions from Agriculture. One of the candidates for this confounding variable could be the outbreaks of foot and mouth disease (FMD) in the UK and there is evidence that, in the past, FMD outbreaks had affected the tourism industry in the UK (Miller and Ritchie, 2003) (Thompson et al., 2002). In fact Miller and Ritchie (2003) argued that "FMD has much larger adverse effects on tourism than on agriculture." However, further investigation is required to test if FMD is actually the third variable or there might exists other third variables influencing tourism and emissions from Agriculture simultaneously. Reducing emissions from the agriculture sector is important because in the global scale emissions from livestock are believed to be more than the emission from world's cars, trains and planes combined. As a result reduction of emission from agriculture is vital to reduce overall GHG emission to the atmosphere (Gerber et al., 2013).

5.2 Granger Causality Result Analysis for Australia

The Granger causality test has been applied for Australia before and after seasonal adjustment using Census-X13 because Granger causality could falsely identify causal relations from the data due to the seasonal trends existing in the data. In this causal result before seasonal adjustment, there is evidence that tourist numbers for Australia are causing emissions from Industrial Processes and Product Use, Transport and Total excluding and including LULUCF. In addition, there is also reverse causality from emissions to tourism, emissions from transportation, Stationary Energy(Excluding electricity), Total excluding and including and LULUCF have causal effects on tourist numbers. These results, especially causality from emission variables towards tourist variables could be due to the confounding third economic or other types of variables which are causing seasonal trends in the series. However, identifying an indirect relation is also important but if the causal relation is only due to seasonal effects than the result is problematic. To remove the seasonality the Census X-13 filter is applied. After applying the Census X-13, if any causal relation is observed which was not present the test result before is not considered as true causality. The reason is, the filtering process could result in a type I error of causality due to the similar kind of changes in the data. The final result is indicative of tourist numbers for Australia causing emissions from Industrial Processes and Product Use, this result is consistent with the seasonally adjusted and unadjusted data. This causality relation could be due to the increased demand due to tourism which leads to increase industrial production (Page and Connell, 2008, p.42). In the case of Australia, there is evidence of a causal relation of tourism causing emission from Transportation. However, this is the case only before seasonal adjustment. On the other hand, Tourist number caused by emission from transportation exists in both cases of seasonally adjusted and unadjusted data. The reason behind this result could be due to:

1. Availability of transportation somehow influence tourists.
2. Strong influential third variable for emission from transportation and tourist number.

5.2.1 CCM Result Analysis for Australia

Increments in the predictability of one variable to another are indicative of causality. Although CCM output shows an increment in the cross correlation of predictability for most of the emissions and tourist variables for Australia, the only reliable conclusion could be drawn from the CCM causality output of emissions from agriculture and tourists. This is due to the fact that using simplex projection only found the existence of nonlinearity in the data for emissions from agriculture and tourists. The test results of CCM for tourists and emissions from agriculture show that there is no evidence of causal relations from tourist numbers to emissions from agriculture, i.e. tourists in Australia causing emissions from agriculture. However, there is evidence of a causal relation that emissions from Agriculture might be causing tourist numbers to change when CCM has been applied. It has also been found that there is significant evidence of emissions from agriculture having causal relations with tourism for the UK case. Perhaps this causal relation might be due to some economic third variable influencing both tourism and emissions from agriculture at the same time.

5.3 Multispatial CCM Result Analysis for EU

The multispatialCCM causality analysis for 20 EU countries showed that visitors export which is the key measurement of tourism used in this study could be nonlinear deterministic but that the emissions data does not show evidence for nonlinearity so the application of CCM is somewhat unrelaiable. However, in the causality test we do see high prediction values for both directions converging with respect to library length which is indicative a bidirectional causality from tourism to emissions and emissions to tourism. However, it is important to state that- this high prediction value does not necessarily imply bidirectional causal relations as it is mentioned by Clark et al. (2015) that a rapid rise in the prediction ρ with respect to library size L could be due synchrony.A Synchrony effect is when one process influences the process dynamics so strongly that the affected process becomes subordinate to the caused process resulting a bidirectional convergence in prediction value for CCM.

5.4 Nonlinearity in Tourism data

In both of the tests for nonlinearity for Australia and EU countries, the test results using simplex projection are highly suggestive that tourist flow is deterministic nonlinear. The usage of nonlinear methods for tourism forecasts is very widely accepted as they outperform linear forecast methods (Claveria et al., 2015)(Baggio and Sainaghi, 2016). In this study, the usage of simplex projection shows that the tourism demand might be nonlinear deterministic. The usage of nonlinear foresting methods such as simplex projection or s-map and empirical dynamic modelling have already brought some groundbreaking successes for forecasting complex ecosystems (Ye et al., 2015a) (Deyle et al., 2016)(Sugihara, 1994)(Sugihara and Mayf, 1990).

5.5 Contribution to Knowledge

This study has confirmed that there exists causal links between tourist number and emissions from different sectors and that this is causality is differentiated across the economic sectors listed. Tourism dynamics do not equally affect all the sectors of emissions e.g. in the UK tourism seems to affect emissions from waste management. This identification of causal links between tourism and different sectors of emissions was not identified or analysed before. Also, another important understanding is, resource usage by the tourism industry might be affecting different sources of emissions in different countries. In this research, it has been found that tourism affects different sources of emissions in the UK than in Australia. This finding will help to build better tourism carbon footprint models on a country by country basis. Before estimating carbon footprint for tourism, this types of causal analysis could be done to identify which sectors are more influenced by tourism in terms of emissions on a country by country basis.

Usage of Convergent Cross Mapping is new to tourism research but it has already been applied in climate science and it has been shown that tourist data might be highly nonlinear. The usage of dynamical modelling is new in tourism dynamics.

This research has compared two statistical causality analysis methods, Granger causality, and Convergent Cross Mapping. The differences and applicability discussed and identified in this study and will help future causality analysis research.

Another contribution is to apply multispatial CCM by considering different countries as multiple replications of the same dynamical system in tourism emissions causality analysis. This approach could be used to identify causality instead of using panel Granger causality analysis.

Chapter 6

Conclusion

6.1 Conclusion

This research reveals several connections between inbound tourism and greenhouse gas emissions. The statistical causality applied in this analysis found that tourism is indeed influencing greenhouse gas emissions. However, not all the sectors of emissions are affected by tourism equally. In addition, the analysis shows that tourism dynamics might be affecting emissions differently in different countries as it has been found that tourism for Australia is affecting different sets of emission sectors than the UK.

Several statistical causal connections from GHG to tourism have been also found. This implies emissions from different sectors have causative effects on tourism. This is shown in the cases of emissions causing tourism that have been found for both the UK and Australia. This finding is important because a change in emissions from different sectors is related to different economic or other confounding variables. These variables could have a profound effect on tourism industries as they might have an effect on the total inflow of inbound tourists for a country. Nevertheless, the causal relation from emissions to tourism could be mainly due to the effect of a third variable rather than having an actual transitive causal relation. Such is the case of emissions from agriculture and tourism in the UK. Where the actual emissions might not be causing tourism as it is intuitively obvious that greenhouse gas emission could not attract tourists on their own. However, that does not necessarily imply that the test result is a false positive. This counter-intuitive causal relation could be due to some underlying economic variable. To explain, lets say GDP for the UK effects overall emissions from Agriculture in the UK, and also affects tourists in a positive way, and that this is a valid hypothesis which could be tested. In such a case, Granger causality will detect causal relations that emissions cause tourists numbers. In this research foot and mouth disease outbreaks in 2001 and

2007 have been proposed as a possible third variable for agriculture towards emission causative relation. Finding a causality relation even if it is due to the third variable is important, because identifying the probable third variable could be helpful for both the tourism industry and reduction of GHG emission.

Another finding of this study is, that inbound tourism for Australia and the EU are both deterministic nonlinear and this study proposes two of the forecasting techniques for touristic variables, called simplex projection and s-map. Both of these methods are based on empirical dynamical modelling and use the theory of deterministic nonlinear dynamical systems. These methods of forecasting could potentially outperform other nonlinear forecasting techniques such as artificial neural networks and, support vector machine for tourism demand forecasting.

The key conclusions of this study are as follows:

1. In the UK tourist numbers are very likely to be causing emissions from the Waste Management sector
2. In the UK tourist numbers might be causing emissions from the Business sector
3. In the UK emissions from Agriculture sector are very likely to be influencing Tourist number. This influence is probably due to an economic third-variable.
4. In Australia tourist numbers are might be causing emissions from Industrial Processes and Product Use sector
5. In Australia emissions from Transportation sector might be somehow influencing tourist number. This influence is probably due to another economic third variable.
6. In Australia emissions from Agriculture and tourist numbers both are nonlinear deterministic and CCM reveals that emissions from the Agriculture sector somehow influencing tourist numbers. This influence is probably due to another economic third variable.
7. In summary, there is statistical evidence that emissions and tourist numbers both have statistical causal influence,and that this causality is differentiated across the economic sectors recorded. The causal effects on tourist numbers from emissions could be explained due to the effects of a third-variable.
8. 'Visitors Exports'(touristic variable) in 20 countries for EU seems to be nonlinear deterministic as it has been seen in the case of Australia that tourist numbers are nonlinear deterministic. As a result, this study proposes a better forecasting approach for touristic variables which is simplex projection based on empirical dynamic modelling.

6.2 Implications

This analysis suggests that moving toward a more sustainable tourism industry will require different approaches in different countries. It has been found that besides tourism's association with emissions from air travel it also affects other sectors of emissions. The tourism industry needs to be focused on identifying how tourists behaviour and use of resources results in greater GHG emissions from these sectors. The sectors which are found to have their emissions increased due to tourists, in this study require more attention from governments and organisations which are working to mitigate climate change. To reduce tourism's association with carbon emissions from these sectors requires tourists change in behaviour through educational campaigns or via policies. For example, educational campaigns for tourists has been proposed by Becken (2004) to reduce emissions caused by tourists. Different policies have also been proposed for a reduction of emissions due to tourism, for example, Tol (2007) proposed a carbon tax on international emissions to reduce emissions. Introducing educational schemes for tourists, and policie, focusing on these sectors of emissions, could substantially help the tourism industry to become more sustainable.

Identifying economic sectors of GHG emission found to be causally related to tourism could help build better tourism carbon footprint models. The tourism affected sectors found in this study should be considered in carbon footprint models especially for the UK and Australia to estimate more precise carbon footprint models.

6.3 Future Work

Convergent Cross Mapping is used in this causality analysis but in most of the cases the test results are not reliable due to a failure to conclude that a most of the emission variables are not found to be deterministic nonlinear. Also, for the UK it has been not possible to apply CCM due to the insufficient observations in the time series data. From a theoretical point of view emissions from different sectors consisting of multiple sub-sectors make more sense if they are nonlinear but without the empirical evidence of deterministic nonlinearity in the observed data the CCM result are inconclusive. This reason for not being able to determine nonlinearity could be due to the noise present in the data. The time series data could be further pre-processed in order to reduce the noise and then tested for non-linearity, thus it could reveal the deterministic non-linear skeleton in the data.

More countries could be considered besides the UK and, Australia to analyse tourism's impact on Greenhouse gas emissions. In addition to that, besides considering sectors, sub-sectors of emissions could also be considered.

The World Bank (2015) and World Travel & Tourism Council (2015) provides data for emissions and tourism for most of the countries in the globe. Also, atmospheric carbon dioxide and other economic variables provided by The World Bank (2015) could be used to build a global tourism, emissions and economic model. A global model will allow testing several hypotheses regarding tourism, emissions and the economy on a global scale.

So far empirical modelling has not been applied for tourism demand forecasting and this could be a future work of this study as it has been found that tourist variables for Australia and EU are nonlinear. Applying nonlinear forecasting methods based on a deterministic nonlinear dynamical system such as simplex projection and s-map could outperform other nonlinear forecasting methods.

Appendix A

An Appendix

A.1 Time Series Data

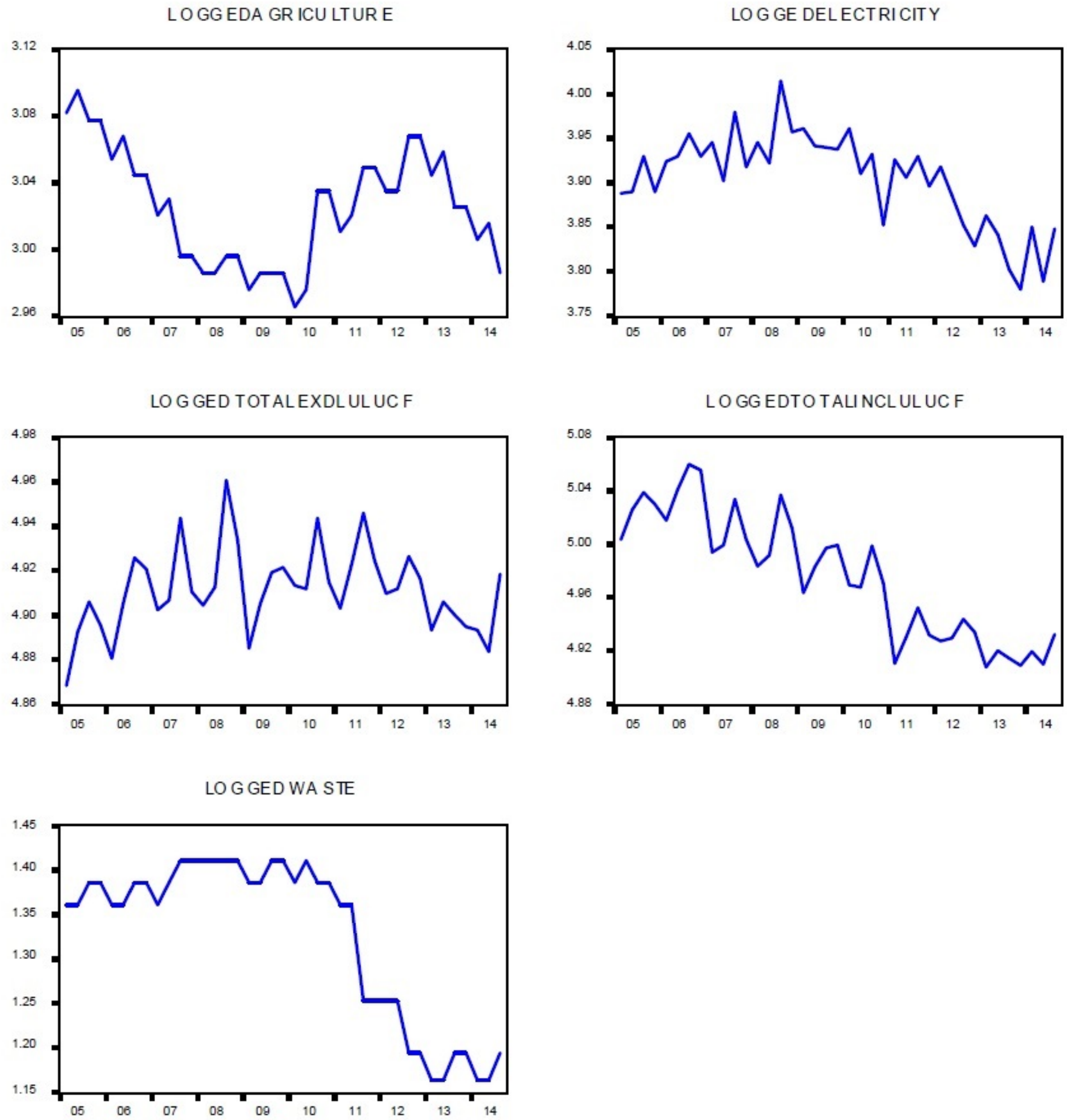

Figure A.1: unadjusted Australian emission and tourist data in level

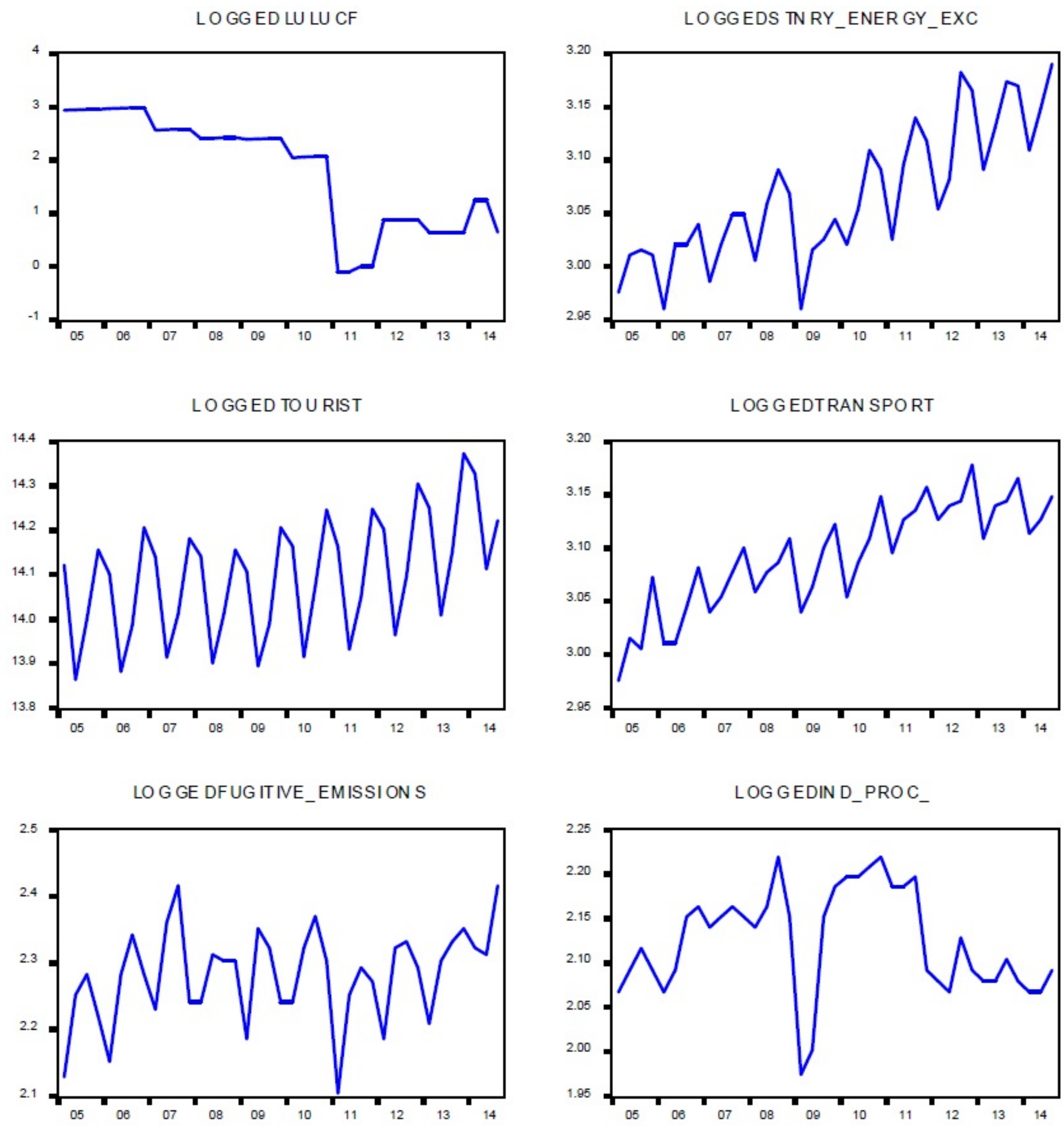

Figure A.2: unadjusted Australian emission and tourist data in level

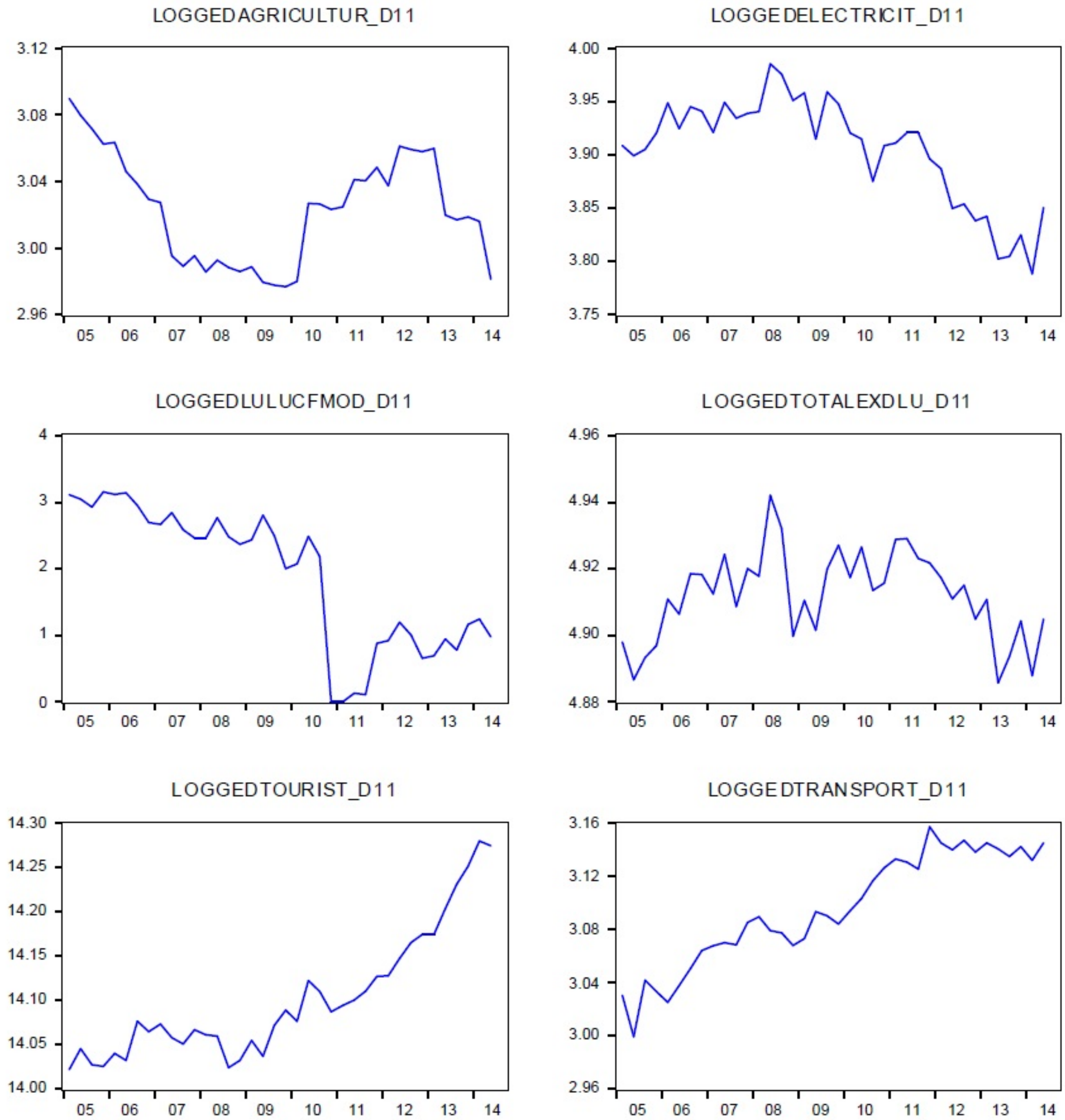

Figure A.3: adjusted Australian emission and tourist data in level

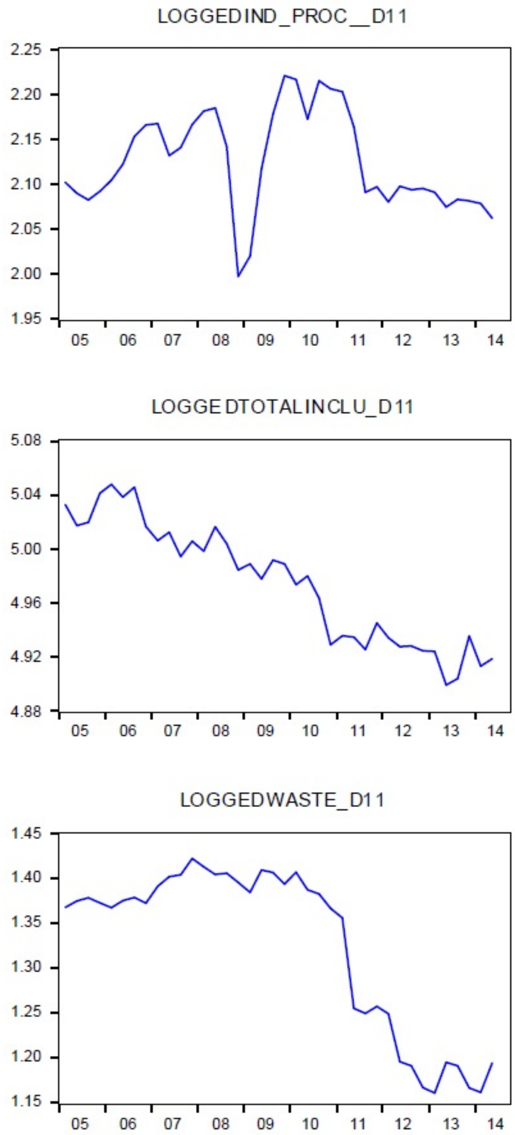

Figure A.4: adjusted Australian emission and tourist data in level

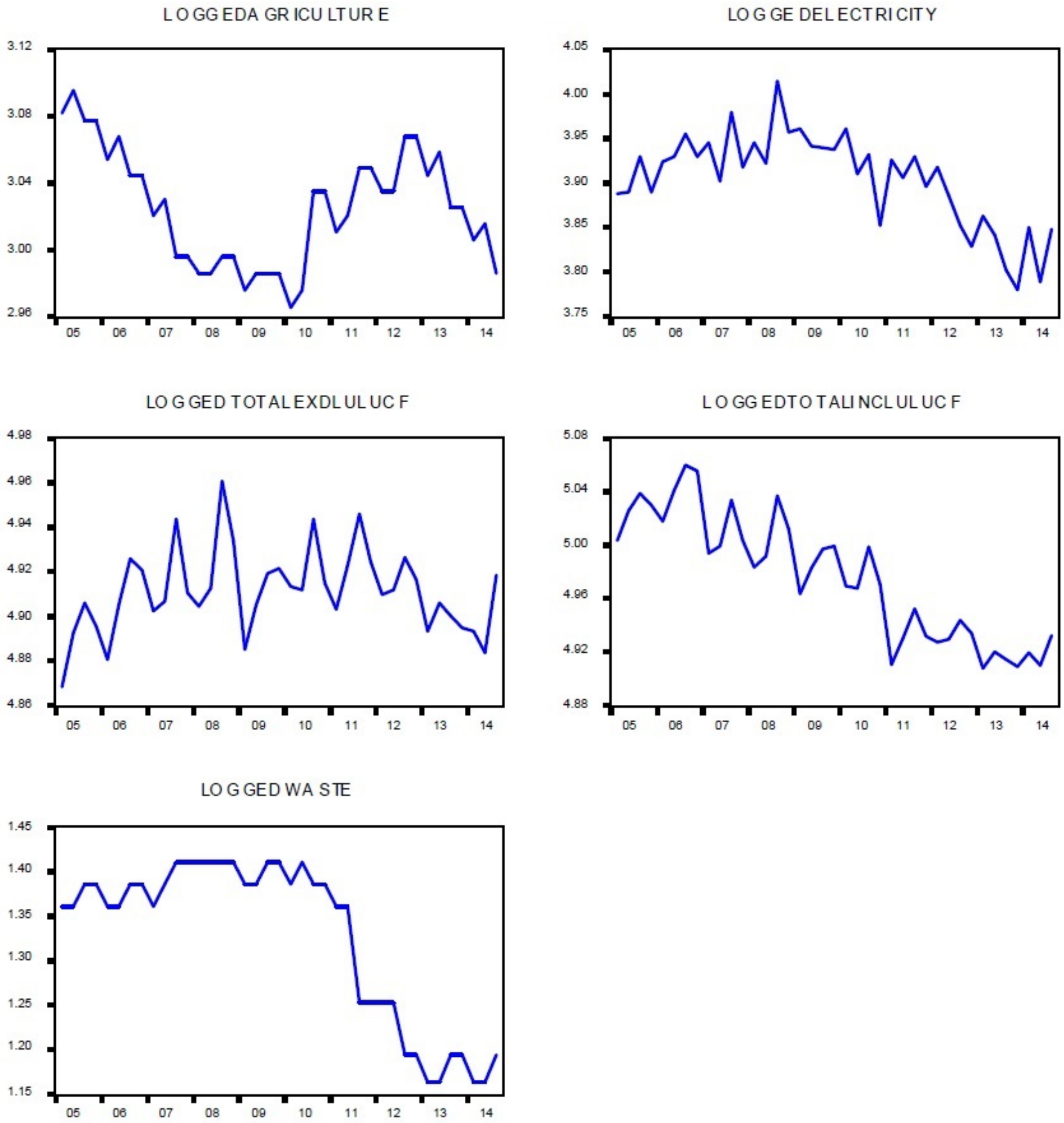

Figure A.5: adjusted Australian emission and tourist data in first difference

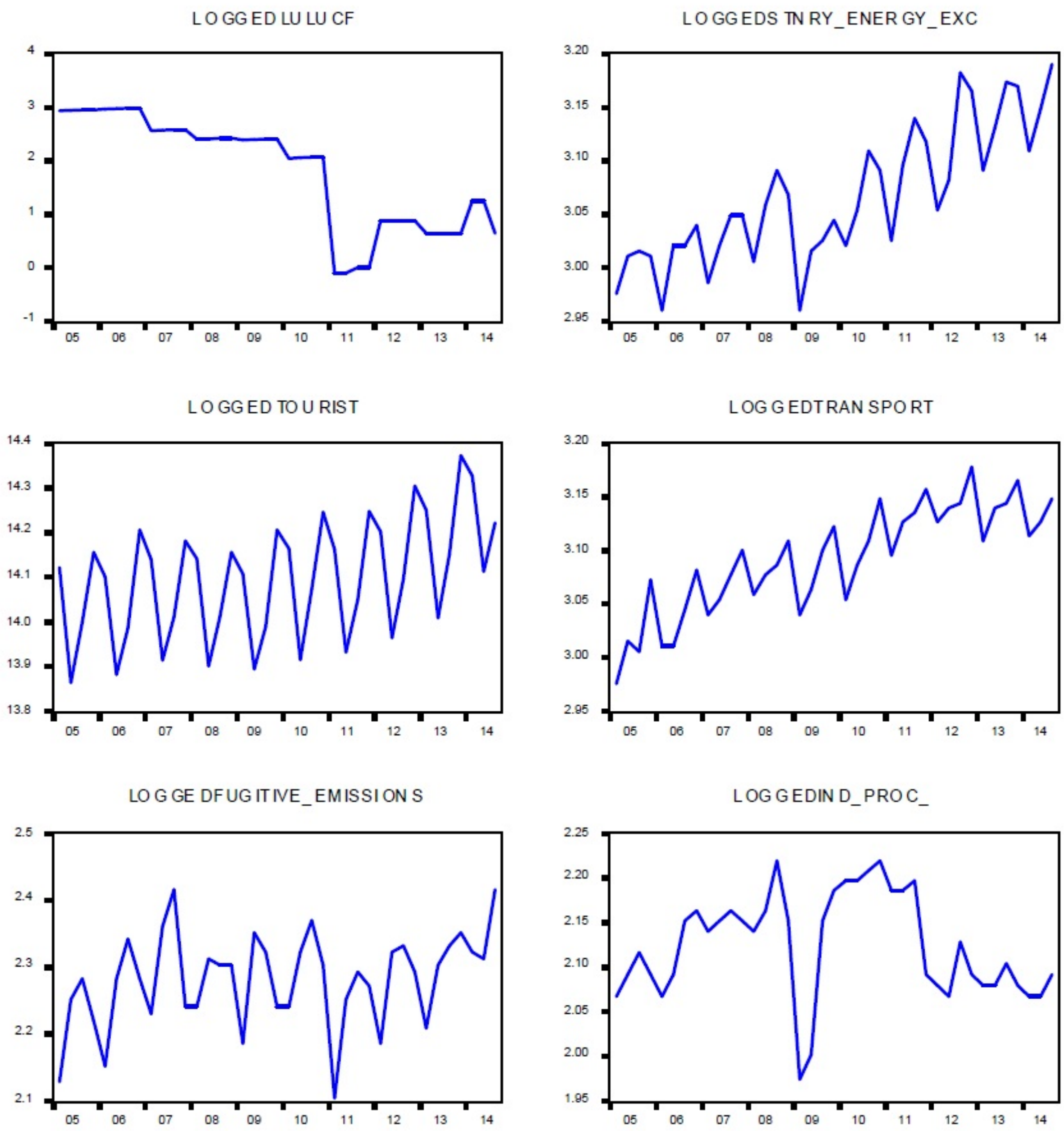

Figure A.6: adjusted Australian emission and tourist data in first difference

Figure A.7: UK emission and tourist data in level

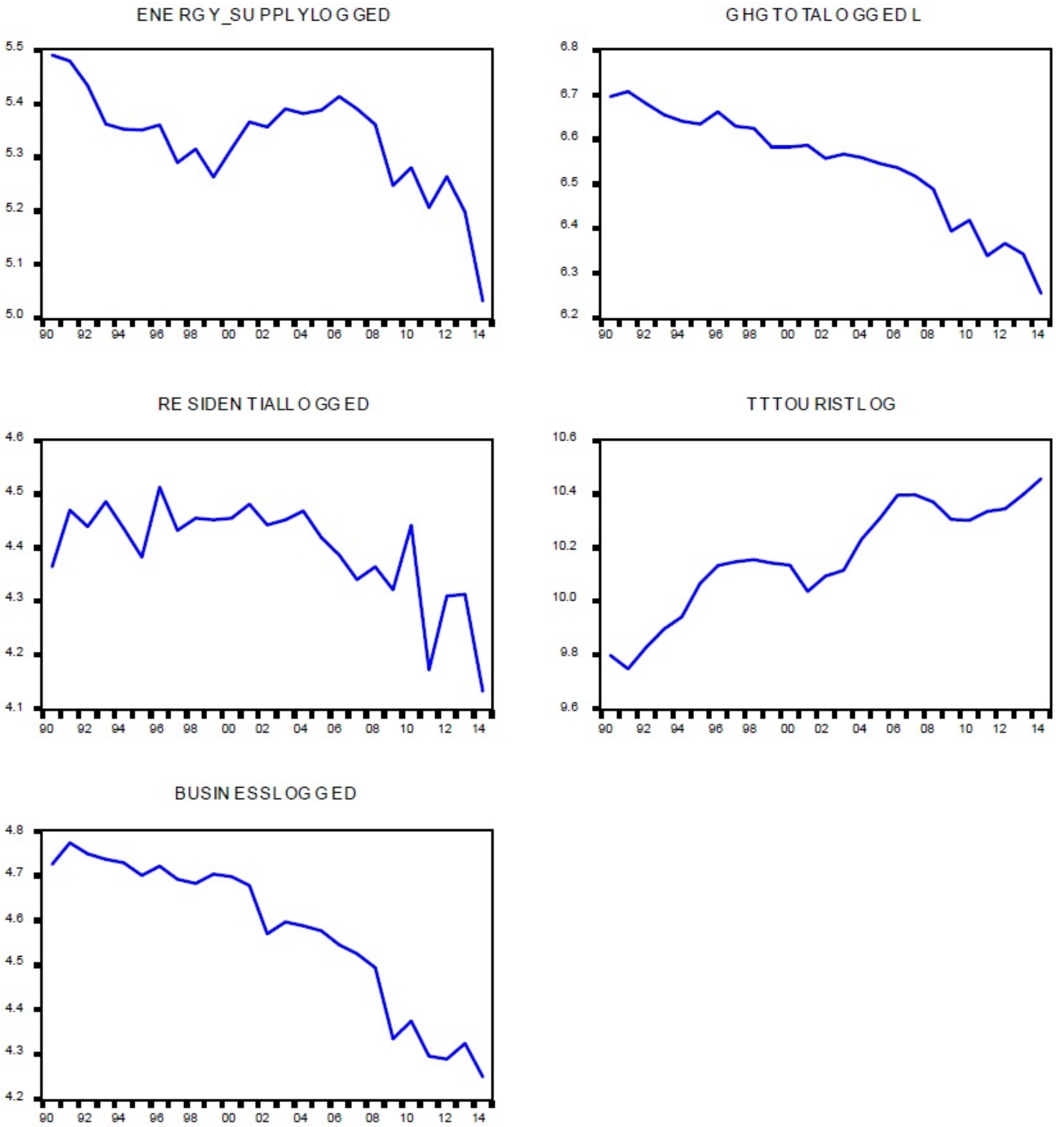

FIGURE A.8: UK emission and tourist data in level

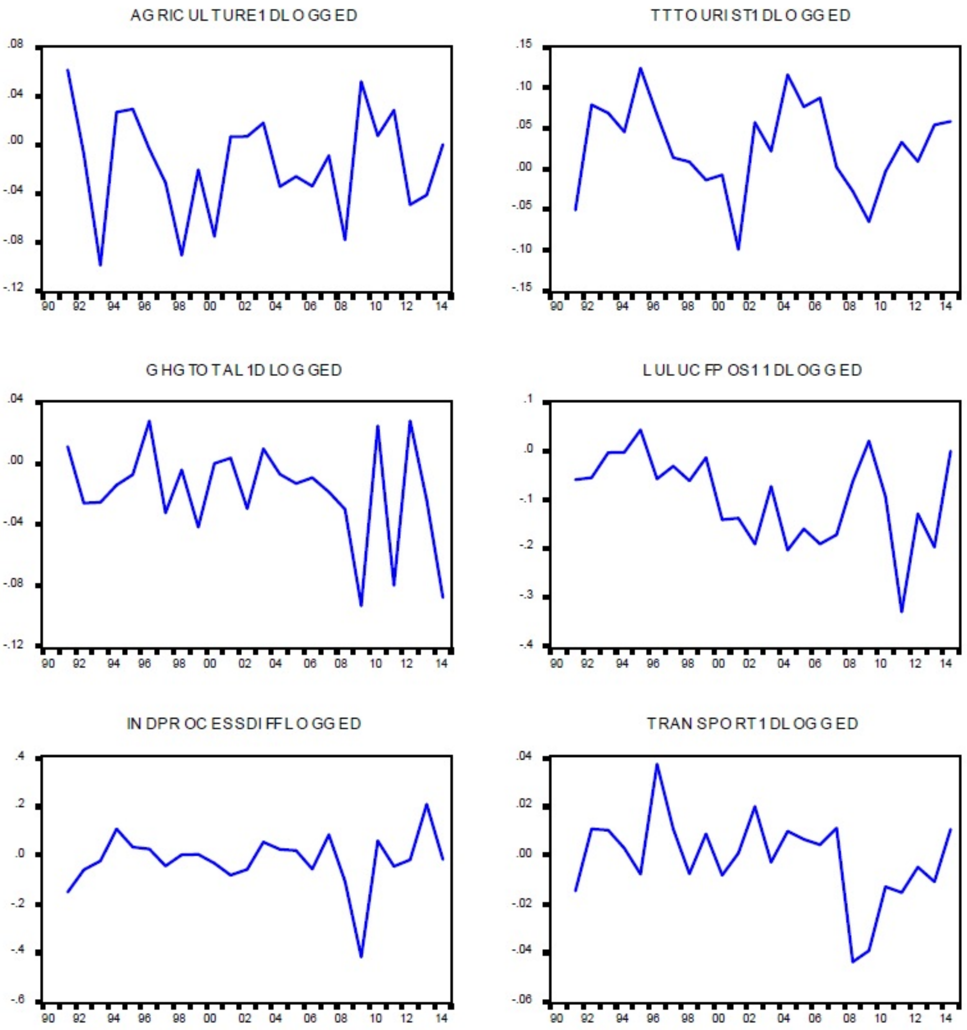

FIGURE A.9: UK emission and tourist data in first difference

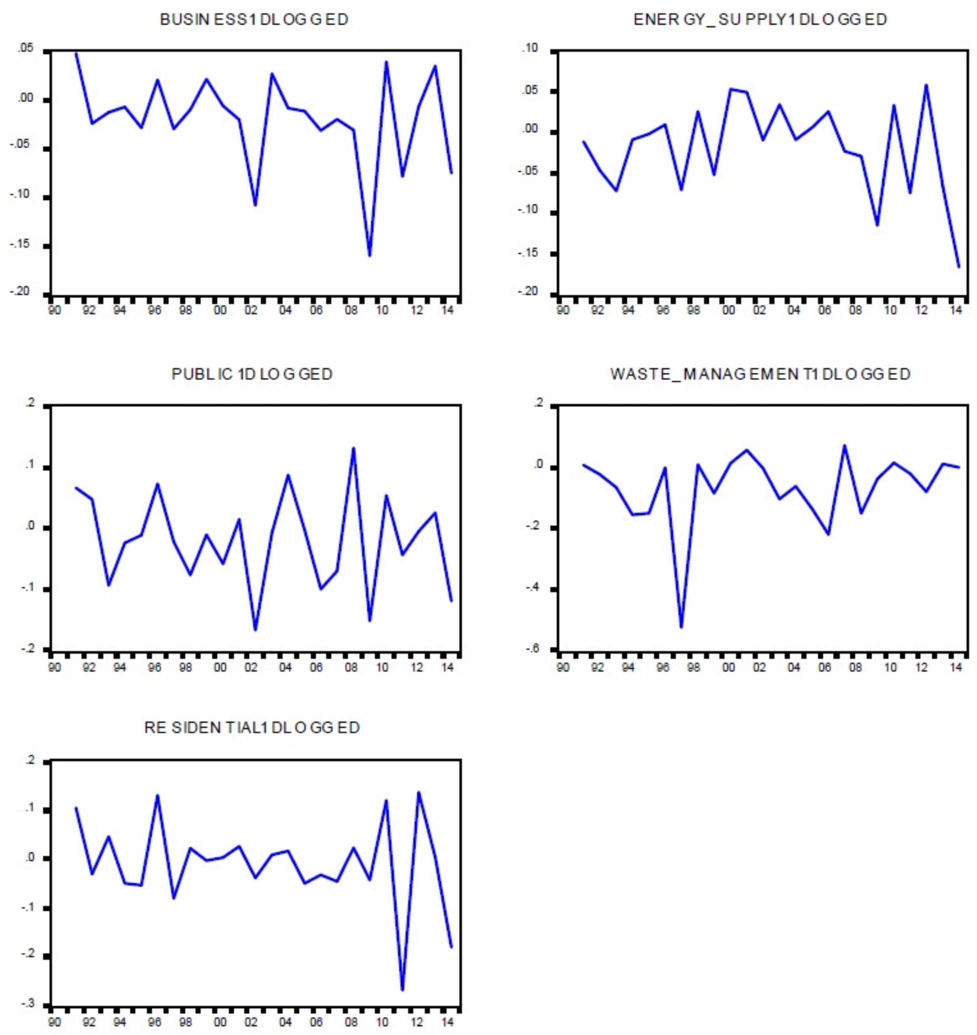

FIGURE A.10: UK emission and tourist data in first difference

A.2 Sectors and Sub sectors for Australia

Category of sources	Sources of Emission
Fuel combustion	
	Fuel combustion
Fugitive emissions	
	Underground mines
	Open cut mines
	Decommissioned underground mines
	Oil or gas exploration
	Crude oil production
	Crude oil transport
	Crude oil refining
	Natural gas production or processing (Other than emissions that are vented or flared)
	Natural gas transmission
	Natural gas distribution
	Natural gas production or processing flaring
	Natural gas production or processing venting
	Carbon capture and storage
Industrial processes	
	Cement clinker production
	Lime production
	Use of carbonates for the production of a product other than cement clinker, lime or soda ash
	Soda ash use
	Soda ash production
	Ammonia production
	Nitric acid production
	Adipic acid production
	Carbide production
	Chemical or mineral production, other than carbide production, using a carbon reductant and carbon anode
	Iron, steel or other metal production using an integrated metalworks
	Ferroalloys production
	Aluminium production
	3N other metals production
	3O Emissions of hydrofluorocarbons and sulphur hexafluoride gases
	3P Sodium cyanide production
Waste	4 Waste
	4A Solid waste disposal on land
	4B Wastewater handling (industrial)
	4C Wastewater handling (domestic or commercial)
	4D Waste incineration
	3N other metals production
	3O Emissions of hydrofluorocarbons and sulphur

Table A.1: Emission category for Australia

A.3 Auto-correlation statistics

A.3.1 Australia

Agriculture VAR(2):
VAR Residual Portmanteau Tests for Autocorrelations

Null Hypothesis: no residual autocorrelations up to lag h

Included observations: 35

Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	0.107865	NA*	0.111038	NA*	NA*
2	0.544034	NA*	0.573640	NA*	NA*
3	6.932844	0.1395	7.561402	0.1090	4
4	10.23709	0.2488	11.29200	0.1857	8
5	15.20177	0.2306	17.08413	0.1465	12
6	17.03478	0.3834	19.29638	0.2536	16
7	19.78713	0.4713	22.73682	0.3019	20
8	23.17676	0.5094	27.13078	0.2984	24
9	24.49244	0.6553	28.90189	0.4175	28
10	24.71651	0.8173	29.21559	0.6082	32
11	26.90198	0.8640	32.40274	0.6404	36
12	39.76227	0.4808	51.97274	0.0973	40
13	40.49588	0.6226	53.13985	0.1626	44
14	42.11939	0.7115	55.84570	0.2038	48
15	45.60706	0.7219	61.94912	0.1626	52
16	49.40584	0.7210	68.94688	0.1147	56

17	50.30408	0.8095	70.69345	0.1627	60
18	51.65365	0.8666	73.47199	0.1956	64
19	54.17281	0.8886	78.98263	0.1706	68
20	55.58615	0.9239	82.28043	0.1911	72

*The test is valid only for lags larger than the VAR lag order.

df is degrees of freedom for (approximate) chi-square distribution

VAR Residual Serial Correlation LM Tests

Null Hypothesis: no serial correlation at lag order h

Included observations: 35

Lags	LM-Stat	Prob
1	3.224443	0.5210
2	3.508650	0.4766
3	6.205216	0.1843
4	3.758829	0.4396
5	7.064009	0.1325
6	2.172131	0.7041
7	3.245958	0.5175
8	6.038823	0.1963
9	2.052945	0.7260
10	0.240090	0.9933
11	3.318359	0.5060
12	21.20654	0.0003

13	1.200376	0.8780
14	4.642299	0.3260
15	4.081160	0.3951
16	7.074328	0.1320
17	3.186663	0.5271
18	2.630934	0.6214
19	4.155896	0.3853
20	6.990556	0.1364

Probs from chi-square with 4 df.

Electricity VEC (1):

VEC Residual Portmanteau Tests for Autocorrelations

Null Hypothesis: no residual autocorrelations up to lag h

Included observations: 36

Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	0.317994	NA*	0.327079	NA*	NA*
2	1.405767	0.9655	1.478839	0.9609	6
3	1.521416	0.9989	1.605001	0.9986	10
4	13.83186	0.4623	15.45425	0.3478	14
5	15.73622	0.6110	17.66576	0.4779	18
6	16.39411	0.7959	18.45523	0.6787	22
7	18.15031	0.8702	20.63534	0.7605	26
8	22.94667	0.8174	26.80209	0.6336	30
9	24.44004	0.8863	28.79325	0.7207	34

10	25.11666	0.9462	29.73011	0.8289	38
11	27.22593	0.9623	32.76746	0.8457	42
12	31.13708	0.9541	38.63418	0.7712	46
13	31.92590	0.9782	39.86887	0.8469	50
14	33.73725	0.9861	42.83290	0.8630	54
15	40.08791	0.9649	53.71973	0.6351	58
16	42.91995	0.9691	58.81740	0.5912	62
17	44.32216	0.9815	61.47422	0.6349	66
18	44.99447	0.9913	62.81885	0.7164	70
19	52.34829	0.9735	78.39164	0.3414	74
20	57.53921	0.9603	90.07122	0.1652	78

*The test is valid only for lags larger than the VAR lag order.

df is degrees of freedom for (approximate) chi-square distribution

VEC Residual Serial Correlation LM Tests

Null Hypothesis: no serial correlation at lag order h

Included observations: 36

Lags	LM-Stat	Prob
1	3.145713	0.5337
2	1.507948	0.8252
3	0.109970	0.9985
4	14.19339	0.0067
5	2.817820	0.5888

6	0.757848	0.9440
7	1.903379	0.7535
8	7.736894	0.1017
9	1.594101	0.8099
10	1.205675	0.8772
11	2.126865	0.7124
12	7.802403	0.0991
13	1.237356	0.8719
14	3.048209	0.5498
15	8.466730	0.0759
16	4.303481	0.3665
17	3.114010	0.5389
18	1.624660	0.8044
19	15.78027	0.0033
20	16.22633	0.0027

Probs from chi-square with 4 df.

Fugitive Emission VAR (3):

VAR Residual Portmanteau Tests for Autocorrelations

Null Hypothesis: no residual autocorrelations up to lag h

Included observations: 34

Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	0.721503	NA*	0.743366	NA*	NA*

2	1.242761	NA*	1.297203	NA*	NA*
3	2.099405	NA*	2.236748	NA*	NA*
4	5.825516	0.2126	6.459674	0.1673	4
5	11.60293	0.1698	13.23319	0.1041	8
6	13.79491	0.3140	15.89489	0.1961	12
7	15.91972	0.4586	18.57058	0.2916	16
8	21.42725	0.3724	25.77272	0.1735	20
9	26.69896	0.3187	32.94225	0.1053	24
10	28.21939	0.4529	35.09619	0.1671	28
11	31.13177	0.5103	39.40145	0.1726	32
12	32.73444	0.6247	41.87831	0.2309	36
13	34.61961	0.7107	44.93049	0.2729	40
14	35.73448	0.8081	46.82576	0.3573	44
15	38.75953	0.8270	52.23901	0.3127	48
16	40.15190	0.8844	54.86904	0.3664	52
17	43.74470	0.8832	62.05464	0.2692	56
18	43.82707	0.9421	62.22968	0.3967	60
19	43.99052	0.9735	62.60016	0.5261	64
20	45.27627	0.9847	65.72270	0.5557	68

*The test is valid only for lags larger than the VAR lag order.

df is degrees of freedom for (approximate) chi-square distribution

VAR Residual Serial Correlation LM Tests

Null Hypothesis: no serial correlation at lag order h

Included observations: 34

Lags	LM-Stat	Prob
1	2.757115	0.5993
2	2.393912	0.6637
3	2.385548	0.6652
4	4.170478	0.3834
5	5.354927	0.2528
6	2.294030	0.6819
7	2.278154	0.6847
8	5.614121	0.2299
9	5.522084	0.2378
10	1.596504	0.8094
11	3.164875	0.5306
12	1.877747	0.7582
13	2.191185	0.7006
14	1.467089	0.8325
15	4.205460	0.3789
16	2.054115	0.7258
17	4.943102	0.2932
18	0.127909	0.9980
19	0.224124	0.9942
20	1.935624	0.7476

Probs from chi-square with 4 df.

Industrial process VEC (2):

VEC Residual Portmanteau Tests for Autocorrelations

Null Hypothesis: no residual autocorrelations up to lag h

Included observations: 35

Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	0.274437	NA*	0.282508	NA*	NA*
2	0.885378	NA*	0.930477	NA*	NA*
3	2.716049	0.8435	2.932772	0.8172	6
4	4.951643	0.8944	5.456830	0.8587	10
5	9.484368	0.7988	10.74501	0.7059	14
6	13.17425	0.7811	15.19831	0.6483	18
7	15.93797	0.8190	18.65296	0.6666	22
8	18.22280	0.8675	21.61479	0.7096	26
9	26.50923	0.6489	32.76959	0.3326	30
10	27.37714	0.7822	33.98466	0.4685	34
11	31.07497	0.7796	39.37733	0.4081	38
12	31.49441	0.8819	40.01561	0.5584	42
13	32.25713	0.9377	41.22902	0.6720	46
14	32.80928	0.9713	42.14929	0.7772	50
15	35.75114	0.9737	47.29753	0.7287	54
16	39.15572	0.9727	53.56914	0.6406	58
17	40.39456	0.9848	55.97798	0.6911	62
18	41.81235	0.9913	58.89697	0.7202	66
19	42.63964	0.9960	60.70667	0.7782	70

20	44.01557	0.9978	63.91718	0.7923	74

*The test is valid only for lags larger than the VAR lag order.

df is degrees of freedom for (approximate) chi-square distribution

LULUCF VAR (1): VAR Residual Portmanteau Tests for Autocorrelations

Null Hypothesis: no residual autocorrelations up to lag h

Included observations: 36

Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	0.014044	NA*	0.014445	NA*	NA*
2	0.281430	0.9910	0.297560	0.9900	4
3	5.581270	0.6940	6.079203	0.6384	8
4	9.964062	0.6191	11.00984	0.5281	12
5	14.71958	0.5453	16.53239	0.4165	16
6	16.24960	0.7010	18.36840	0.5632	20
7	17.70627	0.8170	20.17668	0.6867	24
8	20.50744	0.8453	23.77818	0.6932	28
9	21.94100	0.9090	25.68960	0.7772	32
10	22.69251	0.9588	26.73016	0.8693	36
11	24.83155	0.9712	29.81038	0.8804	40
12	37.95815	0.7271	49.50027	0.2630	44
13	38.91808	0.8221	51.00278	0.3564	48
14	41.53232	0.8504	55.28061	0.3519	52

15	45.22484	0.8480	61.61065	0.2823	56
16	49.43301	0.8330	69.18536	0.1951	60
17	50.57280	0.8891	71.34496	0.2469	64
18	51.76252	0.9283	73.72440	0.2965	68
19	53.82122	0.9461	78.08401	0.2916	72
20	55.20489	0.9653	81.19727	0.3206	76

*The test is valid only for lags larger than the VAR lag order.

df is degrees of freedom for (approximate) chi-square distribution

VAR Residual Serial Correlation LM Tests

Null Hypothesis: no serial correlation at lag order h

Included observations: 36

Lags	LM-Stat	Prob
1	0.174507	0.9964
2	0.263308	0.9921
3	5.378957	0.2506
4	5.089267	0.2783
5	6.717948	0.1516
6	2.003271	0.7352
7	1.753618	0.7810
8	4.763299	0.3125
9	2.320455	0.6770

10	0.928680	0.9204
11	3.366035	0.4985
12	22.85988	0.0001
13	1.691575	0.7922
14	6.165753	0.1871
15	4.833135	0.3049
16	8.030974	0.0905
17	4.100951	0.3925
18	2.462922	0.6513
19	3.714968	0.4460
20	7.334266	0.1192

Probs from chi-square with 4 df.

Stationary energy except electricity, VEC (3).

VEC Residual Portmanteau Tests for Autocorrelations

Null Hypothesis: no residual autocorrelations up to lag h

Included observations: 34

Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	3.706065	NA*	3.818370	NA*	NA*
2	5.879186	NA*	6.127311	NA*	NA*
3	7.018719	NA*	7.377122	NA*	NA*
4	8.357897	0.2130	8.894856	0.1796	6
5	13.06628	0.2200	14.41503	0.1549	10

6	17.25798	0.2427	19.50496	0.1465	14
7	18.87638	0.3995	21.54294	0.2529	18
8	22.61952	0.4235	26.43781	0.2334	22
9	26.62305	0.4293	31.88261	0.1970	26
10	27.63557	0.5897	33.31702	0.3090	30
11	30.05124	0.6617	36.88801	0.3368	34
12	32.41466	0.7249	40.54056	0.3589	38
13	35.09508	0.7659	44.88029	0.3521	42
14	38.00461	0.7930	49.82649	0.3237	46
15	41.24299	0.8065	55.62150	0.2714	50
16	44.52951	0.8174	61.82936	0.2167	54
17	47.24864	0.8425	67.26762	0.1895	58
18	48.46364	0.8955	69.84950	0.2307	62
19	48.99372	0.9419	71.05100	0.3133	66
20	49.76671	0.9680	72.92827	0.3820	70

*The test is valid only for lags larger than the VAR lag order.

df is degrees of freedom for (approximate) chi-square distribution

VEC Residual Serial Correlation LM Tests

Null Hypothesis: no serial correlation at lag order h

Included observations: 34

Lags LM-Stat Prob

1	8.283181	0.0817
2	4.086367	0.3944
3	2.530003	0.6393
4	2.498461	0.6449
5	5.209904	0.2664
6	6.558506	0.1611
7	1.539129	0.8197
8	5.019897	0.2853
9	4.942751	0.2932
10	1.145440	0.8870
11	2.733673	0.6033
12	2.450634	0.6535
13	3.354560	0.5003
14	3.916742	0.4174
15	4.081719	0.3951
16	4.425015	0.3515
17	6.442979	0.1684
18	2.251627	0.6896
19	0.982634	0.9124
20	2.481792	0.6479

Probs from chi-square with 4 df.

Total excluding LULUCF VAR (1):

VAR Residual Portmanteau Tests for Autocorrelations

Null Hypothesis: no residual autocorrelations up to lag h

Included observations: 36

Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	0.230960	NA*	0.237559	NA*	NA*
2	0.951040	0.9171	0.999997	0.9098	4
3	2.522325	0.9607	2.714126	0.9510	8
4	12.24784	0.4260	13.65533	0.3233	12
5	16.58555	0.4129	18.69267	0.2849	16
6	18.40841	0.5605	20.88011	0.4042	20
7	20.03317	0.6949	22.89705	0.5259	24
8	21.57703	0.8005	24.88201	0.6342	28
9	26.20536	0.7545	31.05311	0.5143	32
10	27.23389	0.8534	32.47723	0.6369	36
11	28.77104	0.9067	34.69073	0.7077	40
12	29.62237	0.9523	35.96773	0.8002	44
13	33.42806	0.9454	41.92446	0.7189	48
14	34.47408	0.9709	43.63613	0.7888	52
15	39.61462	0.9523	52.44849	0.6101	56
16	41.61381	0.9661	56.04702	0.6209	60
17	42.90621	0.9803	58.49578	0.6707	64
18	43.66596	0.9905	60.01527	0.7440	68
19	49.87578	0.9782	73.16548	0.4395	72
20	51.74026	0.9851	77.36057	0.4350	76

*The test is valid only for lags larger than the VAR lag order.

df is degrees of freedom for (approximate) chi-square distribution

VAR Residual Serial Correlation LM Tests

Null Hypothesis: no serial correlation at lag order h

Included observations: 36

Lags	LM-Stat	Prob
1	1.924593	0.7496
2	0.742438	0.9460
3	1.633682	0.8027
4	10.59315	0.0315
5	5.539748	0.2363
6	2.372806	0.6675
7	1.921661	0.7502
8	2.059318	0.7248
9	4.885250	0.2993
10	1.179708	0.8814
11	1.934420	0.7478
12	0.934944	0.9195
13	5.300658	0.2578
14	1.975751	0.7402
15	6.510806	0.1641
16	3.664493	0.4533

17	2.585553	0.6294
18	1.026832	0.9057
19	11.83277	0.0186
20	3.825943	0.4301

Probs from chi-square with 4 df.

Total including LULUCF VAR (1):

VAR Residual Portmanteau Tests for Autocorrelations

Null Hypothesis: no residual autocorrelations up to lag h

Date: 09/11/15 Time: 23:14

Sample: 3/01/2005 9/01/2014

Included observations: 36

Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	0.302457	NA*	0.311099	NA*	NA*
2	2.000810	0.7356	2.109354	0.7157	4
3	3.267346	0.9165	3.491031	0.8999	8
4	10.69102	0.5556	11.84266	0.4584	12
5	11.43214	0.7821	12.70332	0.6943	16
6	15.07624	0.7720	17.07624	0.6480	20
7	15.37829	0.9092	17.45119	0.8288	24
8	17.76884	0.9318	20.52477	0.8446	28
9	18.81258	0.9689	21.91642	0.9096	32
10	21.66852	0.9716	25.87079	0.8940	36

11	27.52543	0.9328	34.30475	0.7238	40
12	31.33395	0.9242	40.01752	0.6430	44
13	32.58747	0.9566	41.97955	0.7168	48
14	34.24796	0.9728	44.69673	0.7538	52
15	39.90093	0.9488	54.38753	0.5361	56
16	44.43735	0.9337	62.55308	0.3857	60
17	45.45074	0.9617	64.47320	0.4599	64
18	46.17222	0.9804	65.91615	0.5490	68
19	51.23766	0.9696	76.64296	0.3321	72
20	57.04630	0.9487	89.71241	0.1346	76

*The test is valid only for lags larger than the VAR lag order.

df is degrees of freedom for (approximate) chi-square distribution

VAR Residual Serial Correlation LM Tests

Null Hypothesis: no serial correlation at lag order h

Included observations: 36

Lags	LM-Stat	Prob
1	3.450828	0.4854
2	1.649185	0.7999
3	1.348865	0.8530
4	8.984059	0.0615
5	1.000085	0.9098

6	5.383261	0.2502
7	0.436701	0.9794
8	2.944735	0.5671
9	1.353423	0.8522
10	4.095657	0.3932
11	10.02121	0.0401
12	6.777640	0.1481
13	1.820102	0.7688
14	2.278299	0.6847
15	9.513181	0.0495
16	8.298607	0.0812
17	1.984319	0.7386
18	1.307071	0.8602
19	10.57100	0.0318
20	16.09614	0.0029

Probs from chi-square with 4 df.

Transport VAR (3):

VAR Residual Portmanteau Tests for Autocorrelations

Null Hypothesis: no residual autocorrelations up to lag h

Included observations: 34

Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	df

1	0.440603	NA*	0.453955	NA*	NA*
2	1.083549	NA*	1.137085	NA*	NA*
3	1.573774	NA*	1.674751	NA*	NA*
4	3.767137	0.4384	4.160562	0.3847	4
5	8.154326	0.4185	9.304163	0.3173	8
6	9.093787	0.6949	10.44494	0.5770	12
7	16.09306	0.4465	19.25883	0.2555	16
8	19.30420	0.5021	23.45802	0.2669	20
9	23.42661	0.4947	29.06450	0.2177	24
10	27.43287	0.4948	34.74003	0.1776	28
11	29.45168	0.5961	37.72436	0.2239	32
12	32.76653	0.6232	42.84730	0.2009	36
13	35.26309	0.6832	46.88936	0.2108	40
14	36.25971	0.7901	48.58362	0.2935	44
15	38.14495	0.8449	51.95719	0.3224	48
16	44.00001	0.7771	63.01675	0.1408	52
17	44.18054	0.8734	63.37782	0.2324	56
18	45.50429	0.9171	66.19079	0.2719	60
19	50.07161	0.8986	76.54337	0.1353	64
20	51.35271	0.9339	79.65463	0.1577	68

*The test is valid only for lags larger than the VAR lag order.

df is degrees of freedom for (approximate) chi-square distribution

VAR Residual Serial Correlation LM Tests

Null Hypothesis: no serial correlation at lag order h

Included observations: 34

Lags	LM-Stat	Prob
1	1.275289	0.8656
2	1.664108	0.7972
3	1.070164	0.8990
4	1.947079	0.7455
5	4.670463	0.3228
6	0.912710	0.9227
7	7.386145	0.1168
8	3.920024	0.4169
9	5.517349	0.2382
10	5.731936	0.2201
11	2.655950	0.6169
12	5.354979	0.2528
13	4.039920	0.4006
14	1.737114	0.7840
15	4.652180	0.3249
16	9.430073	0.0512
17	0.321424	0.9884
18	4.099823	0.3927
19	13.05592	0.0110
20	3.164284	0.5307

Probs from chi-square with 4 df.

Waste VAR (1):

VAR Residual Serial Correlation LM Tests

Null Hypothesis: no serial correlation at lag order h

Date: 09/11/15 Time: 23:30

Sample: 3/01/2005 9/01/2014

Included observations: 36

Lags	LM-Stat	Prob
1	2.384909	0.6654
2	2.063024	0.7242
3	1.820412	0.7687
4	6.991420	0.1363
5	5.748368	0.2187
6	5.804711	0.2142
7	0.695745	0.9519
8	9.105792	0.0585
9	2.813457	0.5895
10	2.152389	0.7078
11	6.381662	0.1724
12	5.377525	0.2507
13	2.146123	0.7089
14	9.513142	0.0495
15	6.701695	0.1525

16	7.492806	0.1120
17	3.416928	0.4906
18	2.108327	0.7158
19	8.386837	0.0784
20	2.107433	0.7160

Probs from chi-square with 4 df.

VAR Residual Portmanteau Tests for Autocorrelations

Null Hypothesis: no residual autocorrelations up to lag h

Included observations: 36

Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	0.111422	NA*	0.114605	NA*	NA*
2	2.258175	0.6884	2.387638	0.6649	4
3	4.101618	0.8478	4.398667	0.8195	8
4	10.73625	0.5516	11.86263	0.4568	12
5	15.50681	0.4879	17.40264	0.3600	16
6	20.09080	0.4523	22.90342	0.2936	20
7	20.74853	0.6535	23.71991	0.4777	24
8	28.08168	0.4601	33.14825	0.2303	28
9	29.87422	0.5745	35.53830	0.3051	32
10	31.57362	0.6791	37.89132	0.3831	36
11	36.49333	0.6289	44.97571	0.2714	40
12	40.37351	0.6278	50.79597	0.2235	44

13	41.05032	0.7510	51.85533	0.3260	48
14	42.50758	0.8233	54.23993	0.3891	52
15	46.82075	0.8040	61.63394	0.2816	56
16	50.03419	0.8170	67.41814	0.2384	60
17	50.65107	0.8875	68.58696	0.3246	64
18	51.14881	0.9366	69.58244	0.4240	68
19	54.77061	0.9348	77.25213	0.3146	72
20	55.25791	0.9649	78.34856	0.4042	76

*The test is valid only for lags larger than the VAR lag order.

df is degrees of freedom for (approximate) chi-square distribution

A.3.2 UK

Energy Supply VAR(1)

VAR Residual Portmanteau Tests for Autocorrelations

Null Hypothesis: no residual autocorrelations up to lag h

Sample: 1990 2014

Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	0.135781	NA*	0.141953	NA*	NA*
2	2.067884	0.7233	2.258066	0.6884	4
3	4.313378	0.8278	4.840383	0.7745	8
4	5.478101	0.9401	6.250312	0.9029	12
5	13.25324	0.6542	16.18521	0.4401	16
6	16.69614	0.6726	20.84326	0.4064	20

7	17.37510	0.8322	21.81925	0.5901	24
8	23.19303	0.7233	30.74009	0.3287	28
9	24.18322	0.8377	32.36682	0.4487	32
10	25.71461	0.8981	35.07620	0.5124	36
11	27.23085	0.9381	37.98233	0.5614	40
12	27.40423	0.9764	38.34485	0.7119	44
13	32.51867	0.9574	50.10806	0.3898	48
14	33.03395	0.9814	51.42490	0.4965	52
15	33.66120	0.9922	53.22824	0.5805	56
16	34.18198	0.9971	54.93936	0.6607	60
17	34.98858	0.9988	58.03132	0.6863	64

VAR Residual Serial Correlation LM Tests

Null Hypothesis: no serial correlation at lag order h

Sample: 1990 2014

Lags	LM-Stat	Prob
1	0.760508	0.9437
2	1.829861	0.7670
3	2.144428	0.7092
4	1.455073	0.8346
5	9.104144	0.0585
6	5.758848	0.2179
7	1.677643	0.7948
8	9.406501	0.0517
9	2.573083	0.6316

10	2.693103	0.6104
11	3.283453	0.5116
12	0.436692	0.9794
13	14.98963	0.0047
14	2.125641	0.7127
15	2.802261	0.5914
16	2.851162	0.5830
17	5.739068	0.2195

Business VAR(1):

VAR Residual Portmanteau Tests for Autocorrelations

Null Hypothesis: no residual autocorrelations up to lag h

Included observations: 23

Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	1.735598	NA*	1.814488	NA*	NA*
2	2.873503	0.5792	3.060765	0.5477	4
3	5.559280	0.6965	6.149409	0.6305	8
4	6.754757	0.8734	7.596565	0.8158	12
5	13.33705	0.6480	16.00728	0.4525	16
6	16.45390	0.6881	20.22419	0.4440	20
7	17.67377	0.8185	21.97775	0.5806	24
8	24.92132	0.6321	33.09067	0.2324	28

9	27.02227	0.7167	36.54222	0.2658	32
10	29.23930	0.7802	40.46466	0.2797	36
11	30.81174	0.8514	43.47849	0.3255	40
12	31.56180	0.9198	45.04680	0.4279	44
13	31.84357	0.9650	45.69489	0.5678	48
14	34.14482	0.9736	51.57585	0.4905	52
15	34.50208	0.9895	52.60296	0.6042	56
16	35.39456	0.9953	55.53542	0.6394	60
17	36.05281	0.9981	58.05871	0.6854	64

*The test is valid only for lags larger than the VAR lag order.

df is degrees of freedom for (approximate) chi-square distribution

VAR Residual Serial Correlation LM Tests

Null Hypothesis: no serial correlation at lag order h

Sample: 1990 2014

Included observations: 23

Lags	LM-Stat	Prob
1	3.926348	0.4161
2	1.348124	0.8532
3	2.794899	0.5927
4	1.076178	0.8980
5	6.279058	0.1793
6	3.857872	0.4256

7	2.002080	0.7354
8	9.314174	0.0537
9	5.914796	0.2056
10	6.985902	0.1366
11	2.656506	0.6168
12	1.298439	0.8616

Probs from chi-square with 4 df.

Transportation VAR(1):

VAR Residual Portmanteau Tests for Autocorrelations

Null Hypothesis: no residual autocorrelations up to lag h

Sample: 1990 2014

Included observations: 23

Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	0.383869	NA*	0.401317	NA*	NA*
2	1.941271	0.7466	2.107043	0.7161	4
3	6.059687	0.6405	6.843222	0.5536	8
4	6.588014	0.8836	7.482776	0.8241	12
5	14.63896	0.5512	17.77010	0.3375	16
6	16.60642	0.6784	20.43196	0.4312	20
7	21.90877	0.5847	28.05408	0.2578	24
8	23.10053	0.7280	29.88145	0.3689	28

9	25.13393	0.8006	33.22203	0.4075	32
10	27.57566	0.8420	37.54201	0.3984	36
11	28.67406	0.9089	39.64728	0.4860	40
12	32.31283	0.9039	47.25562	0.3411	44
13	34.00837	0.9366	51.15537	0.3509	48
14	34.93618	0.9667	53.52643	0.4155	52
15	35.11358	0.9870	54.03646	0.5495	56
16	36.79634	0.9921	59.56554	0.4915	60
17	37.67835	0.9965	62.94658	0.5138	64

*The test is valid only for lags larger than the VAR lag order.

df is degrees of freedom for (approximate) chi-square distribution

VAR Residual Serial Correlation LM Tests

Null Hypothesis: no serial correlation at lag order h

Sample: 1990 2014

Included observations: 23

Lags	LM-Stat	Prob
1	2.860992	0.5814
2	1.496677	0.8272
3	3.843059	0.4277
4	0.448406	0.9783
5	7.408909	0.1158
6	2.220680	0.6952
7	7.405170	0.1160

8	1.294750	0.8623
9	2.360046	0.6699
10	2.810027	0.5901
11	1.419040	0.8409
12	5.633065	0.2283
13	2.877940	0.5785
14	1.938137	0.7471
15	0.531047	0.9704
16	7.100400	0.1307
17	4.648868	0.3253

Probs from chi-square with 4 df.

Residential VAR(1):
VAR Residual Portmanteau Tests for Autocorrelations

Null Hypothesis: no residual autocorrelations up to lag h

Sample: 1990 2014

Included observations: 23

Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	2.556582	NA*	2.672790	NA*	NA*
2	5.313899	0.2566	5.692709	0.2233	4
3	10.05537	0.2612	11.14540	0.1936	8
4	11.08061	0.5220	12.38648	0.4152	12
5	18.39691	0.3012	21.73509	0.1520	16

6	20.50532	0.4267	24.58764	0.2177	20
7	20.94324	0.6421	25.21716	0.3940	24
8	21.78181	0.7913	26.50296	0.5454	28
9	22.43833	0.8952	27.58153	0.6899	32
10	24.22519	0.9326	30.74289	0.7166	36
11	25.20079	0.9672	32.61278	0.7902	40
12	26.24082	0.9846	34.78739	0.8384	44
13	27.20794	0.9932	37.01178	0.8752	48
14	27.68473	0.9977	38.23025	0.9229	52
15	30.75365	0.9976	47.05338	0.7971	56
16	32.89606	0.9983	54.09272	0.6903	60
17	33.69470	0.9994	57.15420	0.7152	64

*The test is valid only for lags larger than the VAR lag order.

df is degrees of freedom for (approximate) chi-square distribution

VAR Residual Serial Correlation LM Tests

Null Hypothesis: no serial correlation at lag order h

Sample: 1990 2014

Included observations: 23

Lags	LM-Stat	Prob
1	6.503431	0.1646
2	3.463189	0.4835
3	5.789088	0.2155

4	1.163025	0.8841
5	11.13228	0.0251
6	3.050421	0.5494
7	0.900226	0.9245
8	1.414586	0.8417
9	1.091337	0.8956
10	3.769501	0.4381
11	1.733721	0.7846
12	1.465359	0.8328
13	1.625496	0.8042
14	1.366685	0.8500
15	13.93110	0.0075
16	8.781408	0.0668
17	3.741159	0.4422

Probs from chi-square with 4 df.

Industrial process VAR(1):

VAR Residual Portmanteau Tests for Autocorrelations

Null Hypothesis: no residual autocorrelations up to lag h

Sample: 1990 2014

Included observations: 23

Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	0.423074	NA*	0.442305	NA*	NA*

2	2.474513	0.6492	2.689119	0.6111	4
3	5.435766	0.7101	6.094560	0.6366	8
4	8.595703	0.7370	9.919747	0.6230	12
5	13.81164	0.6127	16.58456	0.4130	16
6	15.26887	0.7608	18.55610	0.5508	20
7	15.89138	0.8920	19.45095	0.7275	24
8	23.09550	0.7282	30.49728	0.3398	28
9	24.59900	0.8219	32.96731	0.4196	32
10	25.41023	0.9059	34.40257	0.5447	36
11	26.61668	0.9483	36.71493	0.6189	40
12	27.26804	0.9775	38.07687	0.7225	44
13	29.01117	0.9863	42.08606	0.7128	48
14	32.53758	0.9842	51.09801	0.5093	52
15	33.02630	0.9938	52.50307	0.6080	56
16	34.56579	0.9966	57.56140	0.5654	60
17	35.75266	0.9984	62.11107	0.5436	64

*The test is valid only for lags larger than the VAR lag order.

df is degrees of freedom for (approximate) chi-square distribution

VAR Residual Serial Correlation LM Tests

Null Hypothesis: no serial correlation at lag order h

Date: 09/10/15 Time: 18:42

Sample: 1990 2014

Included observations: 23

Lags LM-Stat Prob

1	3.336401	0.5032
2	2.059912	0.7247
3	3.122485	0.5375
4	3.242333	0.5181
5	5.075725	0.2796
6	1.792344	0.7739
7	3.082131	0.5442
8	8.949369	0.0624
9	3.256643	0.5158
10	1.314212	0.8590
11	1.863429	0.7609
12	1.309801	0.8597
13	5.989427	0.1999
14	15.30924	0.0041
15	2.666924	0.6150
16	7.441302	0.1143
17	5.617484	0.2296

Probs from chi-square with 4 df.

Public VAR(3):

VAR Residual Portmanteau Tests for Autocorrelations

Null Hypothesis: no residual autocorrelations up to lag h

Sample: 1990 2014

Included observations: 21

Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	0.941945	NA*	0.989043	NA*	NA*
2	1.736622	NA*	1.867370	NA*	NA*
3	2.643565	NA*	2.925470	NA*	NA*
4	7.162414	0.1276	8.507577	0.0747	4
5	10.60873	0.2249	13.03087	0.1108	8
6	16.39209	0.1739	21.12758	0.0485	12
7	18.29658	0.3068	23.98431	0.0898	16
8	20.19328	0.4459	27.04820	0.1339	20
9	20.75198	0.6533	28.02594	0.2589	24
10	22.25751	0.7692	30.90012	0.3215	28
11	23.80077	0.8515	34.14097	0.3651	32
12	26.67709	0.8709	40.85239	0.2657	36
13	27.98155	0.9239	44.27660	0.2960	40
14	29.32731	0.9563	48.31388	0.3029	44
15	32.27907	0.9602	58.64502	0.1396	48
16	32.68381	0.9834	60.34495	0.1997	52
17	32.81534	0.9943	61.03545	0.2998	56

*The test is valid only for lags larger than the VAR lag order.

df is degrees of freedom for (approximate) chi-square distribution

VAR Residual Serial Correlation LM Tests

Null Hypothesis: no serial correlation at lag order h

Sample: 1990 2014

Included observations: 21

Lags	LM-Stat	Prob
1	2.281654	0.6841
2	1.178701	0.8816
3	1.172113	0.8827
4	4.418254	0.3524
5	3.496398	0.4784
6	8.970106	0.0619
7	3.024063	0.5538
8	4.039598	0.4007
9	1.617101	0.8057
10	4.774923	0.3112
11	4.890674	0.2987
12	4.663975	0.3235
13	2.083242	0.7205
14	8.701594	0.0690
15	12.37847	0.0147
16	1.879806	0.7579
17	0.571551	0.9662

Probs from chi-square with 4 df.

Agriculture VEC (1):

VEC Residual Portmanteau Tests for Autocorrelations

Null Hypothesis: no residual autocorrelations up to lag h

Sample: 1990 2014

Included observations: 23

Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	1.256558	NA*	1.313674	NA*	NA*
2	3.476325	0.7471	3.744848	0.7112	6
3	10.52410	0.3958	11.84979	0.2952	10
4	10.72300	0.7076	12.09056	0.5990	14
5	13.69134	0.7490	15.88344	0.6007	18
6	19.82937	0.5937	24.18784	0.3375	22
7	22.53019	0.6594	28.07027	0.3550	26
8	25.76119	0.6873	33.02446	0.3215	30
9	27.53555	0.7757	35.93948	0.3777	34
10	30.84613	0.7884	41.79666	0.3093	38
11	31.68235	0.8769	43.39942	0.4115	42
12	33.15833	0.9218	46.48555	0.4523	46
13	37.50762	0.9038	56.48894	0.2455	50
14	37.66814	0.9554	56.89913	0.3677	54
15	39.79532	0.9675	63.01480	0.3035	58
16	40.63098	0.9837	65.76054	0.3480	62
17	41.54879	0.9920	69.27880	0.3674	66

*The test is valid only for lags larger than the VAR lag order.

df is degrees of freedom for (approximate) chi-square distribution

VEC Residual Serial Correlation LM Tests

Null Hypothesis: no serial correlation at lag order h

Sample: 1990 2014

Included observations: 23

Lags	LM-Stat	Prob
1	4.330688	0.3631
2	2.082897	0.7205
3	7.498048	0.1118
4	0.201989	0.9952
5	2.922630	0.5709
6	7.376599	0.1173
7	3.453224	0.4850
8	4.362748	0.3591
9	2.537159	0.6380
10	4.766269	0.3121
11	1.337937	0.8549
12	2.140586	0.7099
13	6.119276	0.1904
14	0.398388	0.9826
15	3.263445	0.5147
16	2.628977	0.6217
17	6.125521	0.1900

Probs from chi-square with 4 df.

Waste Management var(2): VAR Residual Portmanteau Tests for Autocorrelations

Null Hypothesis: no residual autocorrelations up to lag h

Date: 10/15/15 Time: 19:08

Sample: 1990 2014

Included observations: 22

Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	0.874176	NA*	0.915804	NA*	NA*
2	1.104334	NA*	1.168977	NA*	NA*
3	4.501513	0.3424	5.102553	0.2769	4
4	9.630039	0.2920	11.37075	0.1816	8
5	15.25400	0.2278	18.64882	0.0974	12
6	20.89443	0.1826	26.40441	0.0486	16
7	25.57515	0.1803	33.26946	0.0315	20
8	25.86854	0.3599	33.73051	0.0896	24
9	28.04481	0.4621	37.41342	0.1100	28
10	31.54071	0.4897	43.82258	0.0795	32
11	32.73051	0.6249	46.20218	0.1187	36
12	34.49555	0.7159	50.08527	0.1318	40
13	36.13442	0.7945	54.09138	0.1417	44
14	36.74415	0.8817	55.76815	0.2058	48
15	37.10534	0.9409	56.90331	0.2976	52

16	38.17514	0.9672	60.82592	0.3064	56

*The test is valid only for lags larger than the VAR lag order.

df is degrees of freedom for (approximate) chi-square distribution

VAR Residual Serial Correlation LM Tests

Null Hypothesis: no serial correlation at lag order h

Date: 10/15/15 Time: 19:10

Sample: 1990 2014

Included observations: 22

Lags	LM-Stat	Prob
1	2.777673	0.5957
2	0.413125	0.9814
3	3.144675	0.5339
4	4.595873	0.3313
5	6.356742	0.1740
6	6.505152	0.1645
7	4.825652	0.3057
8	0.417904	0.9810
9	2.663890	0.6155
10	4.192074	0.3806
11	1.597553	0.8092
12	2.729913	0.6040

13	2.634219	0.6208
14	2.489700	0.6465
15	0.729764	0.9476
16	1.560776	0.8158

Probs from chi-square with 4 df.

LULUCF VEC(1):

VEC Residual Portmanteau Tests for Autocorrelations

Null Hypothesis: no residual autocorrelations up to lag h

Sample: 1990 2014

Included observations: 23

Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	1.164211	NA*	1.217130	NA*	NA*
2	3.382961	0.7595	3.647190	0.7243	6
3	8.467768	0.5832	9.494717	0.4859	10
4	10.40880	0.7317	11.84439	0.6188	14
5	16.75968	0.5397	19.95940	0.3351	18
6	18.34142	0.6856	22.09940	0.4540	22
7	22.36944	0.6683	27.88968	0.3639	26
8	23.82460	0.7799	30.12092	0.4595	30
9	27.03879	0.7960	35.40139	0.4019	34
10	33.49231	0.6779	46.81915	0.1544	38

11	34.28138	0.7956	48.33153	0.2324	42
12	36.61310	0.8374	53.20695	0.2165	46
13	37.23364	0.9094	54.63419	0.3029	50
14	37.83522	0.9534	56.17157	0.3935	54
15	38.75544	0.9756	58.81719	0.4454	58
16	40.87015	0.9825	65.76551	0.3478	62
17	41.95084	0.9909	69.90818	0.3477	66

*The test is valid only for lags larger than the VAR lag order.

df is degrees of freedom for (approximate) chi-square distribution

VEC Residual Serial Correlation LM Tests

Null Hypothesis: no serial correlation at lag order h

Sample: 1990 2014

Included observations: 23

Lags	LM-Stat	Prob
1	2.127872	0.7123
2	1.949000	0.7451
3	4.641802	0.3261
4	2.225159	0.6944
5	6.575371	0.1601
6	2.582912	0.6299

7	6.499036	0.1649
8	2.593876	0.6279
9	3.825002	0.4302
10	9.436726	0.0511
11	3.431528	0.4884
12	10.47767	0.0331
13	1.276263	0.8654
14	3.325053	0.5050
15	10.79770	0.0289
16	6.575765	0.1601
17	4.898598	0.2979

Probs from chi-square with 4 df.

Total VEC(1)

VEC Residual Portmanteau Tests for Autocorrelations

Null Hypothesis: no residual autocorrelations up to lag h

Sample: 1990 2014

Included observations: 23

Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	1.187638	NA*	1.241622	NA*	NA*
2	3.518665	0.7415	3.794651	0.7044	6
3	7.680528	0.6600	8.580793	0.5723	10
4	9.411350	0.8038	10.67600	0.7113	14

5	16.20299	0.5784	19.35421	0.3703	18
6	17.53549	0.7331	21.15700	0.5111	22
7	19.52093	0.8137	24.01108	0.5753	26
8	22.77847	0.8243	29.00597	0.5173	30
9	23.60298	0.9091	30.36052	0.6467	34
10	24.40255	0.9572	31.77514	0.7516	38
11	25.31010	0.9805	33.51462	0.8219	42
12	25.59677	0.9936	34.11401	0.9022	46
13	31.04231	0.9838	46.63876	0.6091	50
14	31.42998	0.9940	47.62945	0.7170	54
15	32.42868	0.9974	50.50073	0.7473	58
16	32.73467	0.9992	51.50612	0.8266	62
17	33.14522	0.9998	53.07989	0.8746	66

*The test is valid only for lags larger than the VAR lag order.

df is degrees of freedom for (approximate) chi-square distribution

VEC Residual Serial Correlation LM Tests

Null Hypothesis: no serial correlation at lag order h

Sample: 1990 2014

Included observations: 23

Lags	LM-Stat	Prob
1	2.955830	0.5652

2	2.317564	0.6776
3	4.326916	0.3636
4	2.336929	0.6741
5	7.891851	0.0956
6	2.483291	0.6476
7	2.684449	0.6119
8	8.720353	0.0685
9	1.867060	0.7602
10	2.453059	0.6531
11	2.898277	0.5750
12	0.562530	0.9671
13	14.92907	0.0049
14	2.152586	0.7077
15	5.619479	0.2294
16	2.643595	0.6191
17	2.991628	0.5592

Probs from chi-square with 4 df.

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