CO_2 EMISSIONS AND INCOME TRAJECTORY IN AUSTRALIA: THE ROLE OF TECHNOLOGICAL CHANGE

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ABSTRACT

This study investigates the relationship between per capita carbon dioxide (CO_2) emissions and per capita GDP in Australia, while controlling for technological state as measured by multifactor productivity and export of black coal. Although technological progress seems to play a critical role in achieving long term goals of CO_2 reduction and economic growth, empirical studies have often considered time trend to proxy technological change. However, as discoveries and diffusion of new technologies may not progress smoothly with time, the assumption of a deterministic technological progress may be incorrect in the long run. The use of multifactor productivity as a measure of technological state, therefore, overcomes the limitations and provides practical policy directions. This study uses recently developed bound-testing approach, which is complemented by Johansen-Juselius maximum likelihood approach and a reasonably large sample size to investigate the cointegration relationship. Both of the techniques suggest that cointegration relationship exists among the variables. The long-run and short-run coefficients of CO_2 emissions function is estimated using ARDL approach. The empirical findings in the study show evidence of the existence of Environmental Kuznets Curve type relationship for per capita CO_2 emissions in the Australian context. The technology as measured by the multifactor productivity, however, is not found as an influencing variable in emissions-income trajectory.

Keywords: carbon emissions, multifactor productivity, income, cointegration

1. INTRODUCTION

In recent years, the issues of emissions reduction policies have garnered profound attention from both policy makers and academic researchers (2009; Garnaut 2008; Ghosh 2010; IPCC 2007a, 2007b; Lantz & Feng 2006; Stern 2008). With highest per capita greenhouse gases (GHGs) emitter among the Annex I countries of the United Nations Framework Convention on Climate Change (UNFCCC), Australia also aims in reducing GHGs emissions in the short and medium run (Department of Climate Change 2008; Garnaut 2008). The growth rate of per capita GHGs emissions for Australia was 16.1 percent during1990-2005 (World Resources Institute 2010). Its per capita carbon dioxide (CO_2) emissions increased from, on average, 9.41 metric tons during 1961-65 to 17.13 metric tons during 2001-05, preceding a peak 17.78 metric tons in 1996-00 (Table 1). Its CO_2 intensity of energy use has increased over time and there was a reduction of the ratio of clean energy production to total energy use during 1996-05 from the previous periods (Table 1 on next page).

The high per capita GHGs emissions in the country is attributed to the reliance on fossil fuels for its energy production, energy intensity and thus economic growth. The country has grown steadily since the last economic downturn in 1990-1991. The average growth rate of real Gross Domestic Product (GDP) of Australia was 3.4 percent during 1991-2000 and 3.1 percent during 2001-2008, which were 21.4 percent and 45.6 percent higher, respectively, than the advanced economies' average (IMF 2009). Over the period of time, the country experienced significant increase in GDP per capita. Therefore, the trade-off between GHGs emissions and output/income is of particular interest to the policy makers and researchers in respect of emissions reduction policies in Australia.

Because GHGs emissions, particularly CO_2 emissions, are linked with economic activities, any direct measures to reduce emissions could limit the progressing pace of economic growth. As such, adoption of direct mitigation measures can be costly for a county like Australia, which has high energy consumption and emission intensity of the energy sector. Nonetheless, the transition towards low carbon economy can only be achieved alongside the goal of sustainable economic growth if technological progress can be achieved. Indeed, theoretical predictions suggest technological progress as a lynchpin to attain low emissions, while maintaining sustainable economic growth (Andreoni & Levinson 2001; López 1994; Stokey 1998).

Table 1: *CO_2 Emissions in Australia*

	Per capita CO_2 emissions *Metric tons*	**Clean energy production** *% of total energy use*	**CO_2 intensity of energy use** *kg (kg of oil equivalent energy use)*
1961-65	9.41	1.48	2.87
1966-70	11.09	1.49	2.94
1971-75	11.70	1.89	2.77
1976-80	13.60	1.82	2.91
1981-85	15.10	1.61	3.20
1986-90	16.00	1.61	3.26
1991-95	16.96	1.60	3.29
1996-00	17.78	1.41	3.14
2001-05	17.13	1.32	3.01

Source: World Bank (2009)

To date, a large number of empirical studies have been conducted to investigate the relationship between various indicators of environmental degradation and income. A considerable number of empirical studies in the past have applied polynomial functions of order two or three between pollution (per capita) and GDP (per capita) or their logarithms (so called *Environmental Kuznets Curve or EKC* studies). These studies have mostly ignored the critical role of technological progress. Some studies include time trend to proxy technological progress (He & Richard 2010; Lantz & Feng 2006; Shafik & Bandyopadhyay 1992). However, as discoveries and diffusion of new technologies may not progress smoothly with time, the assumption of a deterministic technological progress may be incorrect in the long run. Moreover, a time trend also reflects other exogenous factors that exhibit a trend (Shafik 1994). As progresses in the state of technology involve changes in productivity, improvements of multifactor productivity can better be used as a more practical measure of technological progress. Multifactor productivity reflects changes in efficiency in both labour and capital inputs and includes "technical progress, improvement in work force, improvement in management practices, economics of scale, and so on" (Aspden 1990, p. 2). This measurement is consistent with exogenous growth theories, which explains technological progress as a residual factor.

To the best of our knowledge, there is no time series study on CO_2 emissions and income nexus in Australia with controlling for technological state. In general, literature in respect of CO_2 emissions as environmental indicator is relatively sparse as compared with local level pollutants. Unlike local pollutants e.g. local water pollution or sanitation, CO_2 emissions exhibit high abatement cost but lower observable benefits (Arrow et al. 1995; De Bruyn 2000; Dinda 2004). Therefore, studies on local pollutants cannot be replicated in the CO_2 context. Moreover, few studies that focuses on CO_2 emissions, have used the panel data approach, limiting its ability to identify country specific policy issues (Stern et al. 1996). A few single country studies, on the other hand, suffer from the issue of small sample size to investigate the long-run relationships. Also, the use of econometric methodology such as Johansen and Juselius (1990) could be sensitive to small sample and choice of deterministic time trend (Cheung & Lai 1993; Demetrescu et al. 2009). In this paper, to overcome the methodological difficulties, we used bounds test for cointegration developed by Pesaran et al. (2001). In addition, Johansen-Juselius method of cointegration is used for a further robustness check.

The objective of this paper is to investigate the relationship between per capita CO_2 emissions and per capita GDP in Australia, while controlling for technological state and aspect of international trade. The novelty of this research is that it incorporates productivity variable in the empirical CO_2 emissions function, which is unique in the literature. In addition, while some studies included trade as a determinant in CO_2 emissions function, this can only measure the overall impact, if any. As such, carbon exposure of the international trade can better be proxied by export of black coal as it is the major source of CO_2 emissions in Australia.

The rest of the paper is structured as follows: the next section presents the review of literature; section 3 incorporates descriptions on model and data; section 4 provides estimation results and section 5 explains the conclusions and policy implications.

2. REVIEW OF LITERATURE

There has been a considerable amount of empirical studies on the linkages between measures of environmental pollutants and economic growth, specially starting from early 1990s. It was the Grossman and Krueger (1991) who first estimated an inverted U-shaped relationship between a number of pollutants (SO_2 and smoke) and income per capita using a reduced form approach. The relationship was further popularized by Shafik and Bandyopadhyay (1992) and Panayotou (1993). Resembling the Kuznets' hypothesis (Kuznets 1955) on inverted U-shaped relationship between income per capita and income inequality, Panayotou (1993) first coined the observed relationship between environment and income as *environmental Kuznets curve*, shortly *EKC*. EKC assets environmental quality worsens in the early stage of economic growth and improves eventually after a level of income per capita. Therefore, economic growth leads to environmental improvement after the threshold levels of income per capita (Stern 2004). Nonetheless, the evidences are mixed and differ widely across pollutants, use of econometric technique and sample of countries (De Bruyn 2000; Galeotti et al. 2006). Furthermore, the existence of inverted U-shaped relationship has been found in case of only few pollutants, especially which create localize pollution problems like lead, sulphur dioxide, nitrogen oxide and carbon monoxide (Arrow et al. 1995; De Bruyn 2000; Dinda 2004). Conversely, for a global pollutant like CO_2, which does not pose dramatic impact at a local level, the impetus to clean them up is delayed even though income reaches at a higher level. In this paper, we single out the studies on CO_2 emissions because it is the major source of GHGs emissions and perceived as the single most important factor for global warming.

In a seminal paper, Shafik and Bandyopadhyay (1992) estimate EKC for 10 different environmental indicators including CO_2 as part of the background study for the 1992 World Development Report (World Bank 1992). The panel data approach for a sample of 118-153 countries between 1960 and 1989 shows the evidence of an exponential increasing relationship between CO_2 emissions and income within a predicted range. The findings are further affirmed by Shafik (1994). Both Shafik and Bandyopadhyay (1992) and Shafik (1994) explain their findings as "a classic free rider problem" due to the global nature of the costs and lack of incentives to reduce emissions. A time index is included to proxy technological progress, which was found insignificant due to lack of any incentives to reduce CO_2 emissions.

Holtz-Eakin and Selden (1995) apply similar reduced-form and panel data approach to estimate relationship between per capita CO_2 emissions and per capita income to forecast aggregate emissions and their distributions among countries. In the study, while CO_2 emissions seem eventually diminish as income grows, the turning point was observed at a very high level of per capita income (above million $) in log specification.

Stern et al. (1996) outline several of the weaknesses of the early cross-sectional studies on EKC including the estimation of single uni-directional relationship without considering the feedback impacts from the environment to economy and application of the ordinary least squares (OLS) estimation methods in the presence of heteroskedasticity. They argue that both economy and the environment are determined simultaneously, therefore, "estimating single-equation relationships by ordinary least squares where simultaneity exists produces biased and inconsistent estimates" (p. 1155). Stern et al. (1996) further postulate the need of a single country approach and application of both econometric and qualitative historical analyses to provide a fruitful conclusion.

In order to correct for heteroscedasticity and autocorrelation, Cole et al. (1997) employ generalized least square (GLS) for cross-country panel data sets covering CO_2 and a number of other environmental indicators. The possibility of simultaneity effects from the environment to economy was also investigated by testing exogeneity of the income variable. The study also finds the evidence of a monotonically increasing relationship between CO_2 emissions and income within an observed income range. While a linear time trend is included to allow the possibility of technological progress, its inclusion posed little implication for the estimated turning point, hence omitted from the final estimation.

Like Stern et al. (1996), De Bruyn et al. (1998) argue that the traditional panel estimation results may not be applied for individual countries' context over time because of the dynamic process involved. Criticizing the EKC specifications in level, they employed alternative growth model to investigate the emissions and income relationships for CO_2 and two other pollutants, nitrogen oxides (NO_x) and sulphur dioxide (SO_2) for four countries, namely Netherlands, UK, USA and Western Germany. The results from the study suggest that economic growth places positive impacts on emissions growth, whilst reductions of emissions depending on income over time are not apparent. The impact of technological and structural changes, as measured by constant terms, was found relatively low during the period of time. The use of longer time series data and application of error correction modelling was warranted to model technological and structural changes.

Schmalensee et al. (1998) find interesting result of within the sample turning point, reporting the clear evidence of an "inverse U" relationship between per capita CO_2 emissions and per capita income for a set of panel data for the period of 1950-1990. For some OECD countries (the case for Australia was not reported), the peaks in per-capita CO_2 emissions were observed in the 1970s. Given the absence of any notable accord or regulation on CO_2 reduction during the sample period of the study, different stages of economic development and technological frontier between developed and developing countries in the sample, the findings of Schmalensee et al. (1998) mask further debate on EKC studies of CO_2 emissions (Dijkgraaf & Vollebergh 2005). In a recent study, Galeotti et al. (2006) find the evidence of inverted U-shape relationship between per capita CO_2 emissions and income for the OECD countries along with reasonable turning point. The EKC for CO_2 emissions was not evidenced in the case of non-OECD and non-OPEC countries (Galeotti et al. 2006).

Pauli (2003) examines homogeneity assumption for a sample of OECD countries by applying a hierarchical bayes model for a period of 1970-1998, where the first level parameters are country-specific autoregressive. The study finds the evidence of no common EKC for OECD countries. The EKC hypothesis for CO_2 was supported by 12 countries, while 9 countries show the evidence of either an increasing or decreasing relationship and for the remaining 8 countries including Australia no clear conclusion was drawn. Dijkgraaf and Vollebergh (2005) also examine the homogeneous assumption of slope parameter across countries using a new dataset for 24 OECD countries for the period of 1960-1997. They find that the assumption does not hold even in the sample of highly developed countries (OECD in this case), putting doubts on the fixed effects estimations of the EKC concerning CO_2 emissions using conventional models. Dijkgraaf and Vollebergh (2005) suggest that the lack of homogeneity across countries on the EKC for CO_2 is due to differences in international specialization and local circumstances and the lack of coordinated policies.

Lantz and Feng (2006), using a five-region panel data set in Canada over the period of 1970-2000, find that the apparent relationship between CO_2 emissions and GDP per capita disappear once additional variables are added in the model. In addition, both population and technology (measured by time index) variables exhibit significant non-linear relationships with CO_2 emissions. A U-shape relationship between CO_2 emissions and technology suggest a shift from environmental friendly production techniques to CO_2 emissions production process in recent years.

Given the various criticism on cross section and panel data approach, a recent trend has been to excel the single country exposure exploiting the time series characteristics of data. More specifically, as the relationship between CO_2 emissions and income differ across countries based on country level characteristics, time series analyses can only shed light on domestic policy making. The findings from time series analysis differ from country to country. The differences in time series results on the existence of the EKC further suggest that pooling many countries would provide incorrect inferences. Therefore, results from the panel or cross sectional studies are unreliable in the context of formulating domestic policies for an individual country (Egli 2002).

Roca et al. (2001) estimate log linear model for per capita CO_2 emissions as a function of per capita income and shares of both nuclear power and coal in the total primary energy for Spain in the period of 1973-1996. The study finds elasticity coefficient between per capita CO_2 emissions and per capita income is greater than unity, postulating a very strong positive long-run association between them. Square and cubic forms are excluded from the model as they show insignificant coefficients and multicolinearity problems. Friedl and Getzner (2003) also find economic growth as main driving force for CO_2 emissions in Austria, while oil crisis in the mid-1970s places a structural break. Among the various functional forms, a cubic functional form better fits the historical trend of CO_2 emissions reflecting an "N" shape relationship between CO_2 emissions and income. As such, Austria needs to undergo significant policy changes (e.g. price shocks by inducing an ecological tax reform) to fulfil international agreement on carbon reduction. However, the study applies usual DF critical values to identify cointegration relationship and to validate OLS estimation. As actual residuals from the equilibrium relationship is not observable, it would be inappropriate to use the usual DF critical values for the cointegration test. Instead, Mackinnon's (1991) Response Surface Estimation procedure should be used for the purpose (Enders 2004).

Egli (2002), using German data for a period of 1966-1998, finds no relationship between CO_2 emissions and income in the short run. The study, however, finds a significant negative relationship in the long-run but the results are not very robust. This could be due to the limitation of shorter sample size (27 observations in case of CO_2). Lindmark (2002) includes a stochastic trend as an indicator of technology and structural change, and finds that, in contrast with the fixed coefficient over time, it better estimates the CO_2 emissions trajectory in Sweden during 1870-1997. The role of input (e.g. energy, fuel and cement) prices and economic growth on CO_2 emissions are also found significant to explain fluctuations in Swedish emissions. The study further suggests that time specific technology clusters may explain EKC pattern.

Huang et al.(2008) tested EKC hypothesis for GHGs using time series analyses for OECD members of Annex I countries. The study finds little evidence to support EKC hypothesis for GHGs in OECD countries including Australia. However, a limitation of the analysis, as acknowledged by the authors, is to employ a sample for only fourteen years period ranging 1990-2003. Moreover, the study suffers from the problem of omitted variables such as technical development and trade indicators (Huang et al. 2008).

Akbostancl et al. (2009) examine the long-run relationship between CO_2 emissions and income for Turkey using Johansen cointegration technique. While the time series models in the study show long-run relationship between CO_2 emissions and income, they do not support the existence of the EKC hypothesis. Once again, the time series models only include linear, quadratic and cubic forms of income, therefore ignoring the presence of other factors that may lead pollutions to fall. As argued by Carson et al. (1997, p. 434), "the presence of these other factors does not undermine policy interest in whether an environmental Kuznets curve exists, but does presence the possibility that any relationship found between income and pollution is a spurious one."

Applying semi-parametric and flexible non-linear parametric models, He and Richard (2010) find the evidence of monotonically increasing relationship between per capita CO_2 emissions and per capita GDP in Canada. Similar to the findings of Friedl and Getzner (2003), their study reveals that the oil price shock in 1970s has slowed CO_2 emissions growth, at least for a decade. Control variables, such as oil (petrol) price, structural changes as proxies by industrial production over GDP, international trade and population do not seem to play any significant role on the evolution of CO_2 emissions in Canada during 1948-2004. The monotonic relationship between per capita CO_2 emissions and per capita GDP is also supported by Fodha and Zaghdoud (2010) for Tunisia during 1961-2004. Ghosh (2010) finds no evidence of long-run equilibrium relationship or long-run causality between CO_2 emissions and income in India during 1971-2006. One the other hand, Jalil and Mahmud (2009) finds support of the EKC relationship between per capita CO_2 emissions and real income in China over the 1975-2005 period.

3. MODEL, ESTIMATION STRATEGY AND DATA

3.1 Model specification

The discussion above suggests per capita real output as a key determinant of pollutant emissions. However, as discussed in the EKC literature, the relationship between per capita income and pollution is non-linear, necessitating the inclusion of quadratic form of income per capita in the specification. The standard quadratic EKC model can be formulated as:

$$\ln(C / P_t) = f\left\{ \ln(Y / P)_t, \ln(Y / P)^2{}_t,\ Z_t \right\} \tag{1}$$

In model 1, C is the carbon emissions, P is population, Y is real income, Z indicates other explanatory variables and ln represents natural logarithms. Authors like Grossman and Kruger (1991, 1995) adopted cubic EKC in levels; however, as argued by Stern (2004), "this might just be a polynomial approximation to a logarithm curve" (p. 1422). The quadratic EKC model is due to, among others, Holtz-Eakin and Selden (1995) and Stern and Cleveland (2004).

The selection of explanatory variables in the model merit discussions. Theoretically, three structural factors are argued to be responsible to define the CO_2 emissions and income trajectory. These include scale, technological and composition effects (Dinda 2004). More output refers more emissions from production and consumption process, which deteriorates environmental quality. The relationship is expected to be positive. However, as economies grow over time, more resources can be allocated to the emissions reductions efforts. Also, growing income suggests improvement in environmental awareness. Environmental quality also tends to deteriorate as structure of the economy tends to gradually change from agriculture-based to manufacturing but tends to improve as the economy moves again from energy intensive manufacturing sector to services sector.

In model (1), scale effect can be represented by *Y/P* (Stern 2004). Some studies like Shafik and Bandyopadhyay (1992), Cole et al. (1997), Lantz and Feng (2006) and He (2010) include time trend to proxy for technological progress. However, time trend is only a crude measure of technological state and can represent, among others, both technological and other exogenous factors correlated with the trend. As such, even though the inclusion of time index can improve the explanatory power of the model, it fails to provide any practical policy direction. We overcome this shortcoming by employing multifactor productivity index in the market sector as a measure of technological state. We vet in compositional effect by including manufacturing share to GDP. However, inclusion of such variable did not improve the explanatory power of the model and proved insignificant relation with CO_2 emission; therefore, excluded from the model. The insignificant role of sectoral share to GDP is consistent with Lindmark (2002) and Friedl and Getzner (2003).

Finally, some studies also controls for other possible determinants of emission such as trade openness (Friedl & Getzner 2003; Jalil & Mahmud 2009). As CO_2 emissions are attributed to the fossil fuels (about 60 percent of total CO_2 emission), export of black coal is included in the model to capture the notion of international trade, which is denoted by *XC*. The econometric specification of our empirical model derived from model (1) is written as follows:

$$cpc_t = f(ypc_t, ypc_t^{\ 2}, T_t, XC_t) \tag{2}$$

where, *cpc* is the CO_2 emissions metric tons per capita, *ypc* is real GDP per capita and ypc^2 is the square of per capita GDP, *T* represents state of technology, and *XC* represents export of black coal. Subscript "*t*" denotes a time period, i.e., year in this case. All variables in model (2) are in the form of natural logarithm; therefore, the coefficients can be illustrated in terms of elasticities. The logarithm specification is appropriate as it prohibits to become environmental variable as zero or negative (Stern 2004). The annual model is estimated for the period of 1965-2006.

3.2 Estimation strategy

In this paper, in order to investigate the cointegration relationship, we employ (i) bound testing approach based on autoregressive distributed lag model (ARDL) introduced by Pesaran and Shin (1999) and Pesaran et al. (2001), and (ii) full information maximum likelihood test developed by Johansen (1988) and Johansen and Juselius (1990). Two alternative methods are employed to check further robustness of the cointegration analysis.

It is suggested that the small sample properties of the bound testing approach for cointegration test are far superior to the conventional multivariate cointegration procedure (Fosu & Magnus 2006; Narayan & Smyth 2005; Narayan & Narayan 2005; Pesaran et al. 2001; Sari et al. 2008). Pesaran and Shin (1999) have shown that the ARDL based estimators of the long-run coefficients are super consistent in small sample size. Moreover, apart from making valid inference on long-run coefficients, ARDL approach allows to apply general-to-specific modelling technique to estimate consistent parameters on short-run effects.

ARDL technique involves estimating a dynamic model, which incorporates the lags of the dependent variable and the lagged and contemporaneous values of the independent variables. Accordingly, using the ARDL approach, the long-run and short-run relationship among the variables can be specified as follows:

$$\Delta cpc_t = \lambda_1 + \sum_{i=1}^{r}\alpha_{1,i}\Delta cpc_{t-i} + \sum_{i=0}^{r}\alpha_{2,i}\Delta ypc_{t-i} + \sum_{i=0}^{r}\alpha_{3,i}\Delta ypc^2{}_{t-i} + \sum_{i=0}^{r}\alpha_{4,i}\Delta T_{t-i} + \sum_{i=0}^{r}\alpha_{5,i}\Delta XC_{t-i}$$
$$+ \beta_1 cpc_{t-1} + \beta_2 ypc_{t-1} + \beta_3 ypc^2{}_{t-1} + \beta_4 T_{t-1} + \beta_5 XC_{t-1} + \eta_{1,t} \quad (3)$$

Formulation of an ARDL model suggests that the variables should either be integrated to order zero, i.e. I(0) or integrated to order 1, i.e. I(1) but not integrated to order 2 i.e. I(2) (Narayan 2005; Pesaran et al. 2001). In equation 3, the long-run (cointegration) among the variables can be traced by applying joint significance restricting all estimated coefficients of lagged level variables. The null hypothesis of no cointegration among the variables is $H_0 : \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = 0$. The hypotheses can be tested by applying general *F*-statistics and comparing them with critical values in Narayan (2005). The critical F values provided by Narayan (2005) are preferred than the values provided by Pesaran et al. (2001) as the former is suited for a sample size ranging 30-80 as compared with 500-1000 observations by the latter. The bound testing approach implies rejection of the null if the computed F statistics is higher than the upper bound of the critical values (see, Pesaran et al. 2001,for details on bound testing procedure).

On the other hand, Johansen (1988) and Johansen and Juselius (1990) cointegration test rely heavily on the relationship between rank of a matrix, i.e. long-run matrix and can explore the possibility of multiple cointegrating vectors using likelihood ratio principle. As this approach has been used extensively in the applied work, we evade specification details here for the sake of scarcity of space. The presence and number of cointegration vector(s) is identified using two different likelihood ratio tests – one is based on trace statistics and the other on maximum eigenvalue (See, Johansen 1995; Johansen & Juselius 1990). Theoretical and practical background of the tests are given by Enders (2004). We use two statistics (trace and maximum eigenvalue) to test for cointegration.

Once the cointegration relationship is confirmed, the long run ARDL model for cpc_t can be estimated as:

$$cpc_t = \lambda_2 + \sum_{i=1}^{r}\delta_{1,i} cpc_{t-i} + \sum_{i=0}^{r}\delta_{2,i} ypc_{t-i} + \sum_{i=0}^{r}\delta_{3,i} ypc^2{}_{t-i} + \sum_{i=0}^{r}\delta_{4,i} T_{t-i} + \sum_{i=0}^{r}\delta_{5,i} XC_{t-i} + \eta_t \quad (4)$$

Finally, a conventional error correction model (ECM) can be estimated to investigate the short-run relationship. The ECM model can be written as:

$$\Delta cpc_t = \lambda_1 + \sum_{i=1}^{r}\alpha\zeta_{1,i}\Delta cpc_{t-i} + \sum_{i=0}^{r}\zeta_{2,i}\Delta y_{t-i} + \sum_{i=0}^{r}\zeta_{3,i}\Delta y^2{}_{t-i} + \sum_{i=0}^{r}\zeta_{4,i}\Delta T_{t-i} + \sum_{i=0}^{r}\zeta_{5,i}\Delta XC_{t-i} + vecm_{t-1} + \eta_t \quad (5)$$

where, *v* represents adjustment coefficient and ecm_{t-1} is the cointegration vectors derived from the long-run relationship estimated in model (2).

3.2 Data

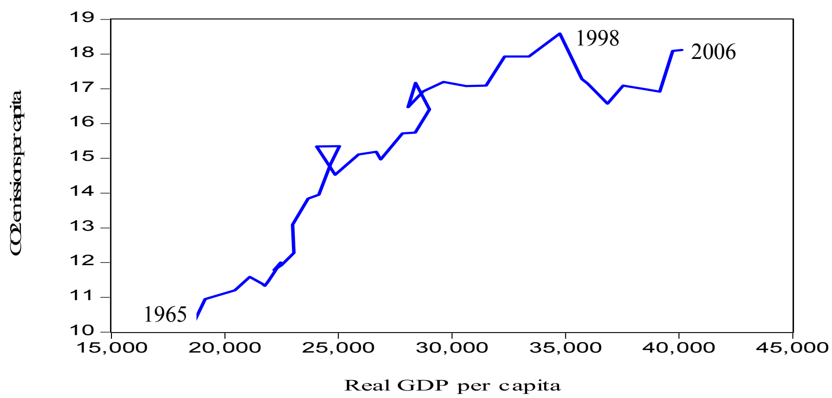
Data for per capita CO_2 emissions (metric tons) and per capita GDP (constant 2007 local currency) are collected from the World Development Indicators (WDI) CD-ROM 09 (World Bank 2009). The CO_2 emissions data in the WDI are those of stemming from the burning of fossil fuels and the manufacture of cement. They include CO_2 produced during consumption of solid, liquid and gas fuels and gas flaring. WDI compiles CO_2 data from three different sources, i.e. Carbon Dioxide Information Analysis Center, Environmental Sciences Division and Oak Ridge National Laboratory, Tennessee, United States. Multifactor Productivity Index (1989-90=100) of Australian Market Sector[1], which has been computed by considering combined factor inputs of labour and capital, is compiled from ABS (1996)

[1] The market sector comprises 12 out of 17 industries under Australian and New Zealand Standard Industrial Classification (ANZSIC) system. The 12 industries are, Agriculture, forestry & fishing; Manufacturing; Electricity, gas & water; Construction; Wholesale trade; Retail trade; Accommodation, cafes & restaurants; Transport and storage; Communication services; Finance & insurance; and Cultural and recreational services. See ABS (2007) for details.

and ABS (2007). Data for export of black coal (sum of coking and steaming) in physical units are collected from the ABARE (2009).

Figure 1 shows the development plane trajectory where per capita CO_2 emissions (metric tons) are plotted relative to per capita GDP (constant AUS$)) in Australia during 1965-2006 (Moomaw & Tullis 1994; Unruh & Moomaw 1998). It is apparent from the figure that CO_2 emissions per capita show a monotonically increasing pattern with GDP per capita until recently. The peak in the figure represents at about A$35,000 in 1998, the year after which CO_2 emissions per capita seems to decline with an increase in per capita GDP before rising again in the most recent years. While this type of declining trend after a threshold point can indicate an existence of inverted-U or an EKC type relationship, however, no clear cut conclusions regarding the existence of EKC can be made as there are several other factors except per capita GDP that may affect per capita CO_2 emissions. Having these initial observations, we go for econometric analyses, which are presented in next sections.

Figure 1: ***Historical pattern of per capita CO2 emissions and per capita GDP***



4.0 ESTIMATION

Problems of spurious regression may arise when time series data is employed in the level or non-stationary form. Therefore, it is necessary to check the stationary properties of the variables to avoid spurious regression. Stationary properties of the data are investigated using three different unit-root tests, namely, Augmented Dicky-Fuller (ADF), Dicky-Fuller GLS (DF-GLS) and Phillips-Perron (PP) tests. The DF-GLS test is implemented along with the conventional DF, as the former performs better in the case of small sample size and power (Elliott et al. 1996). The null hypothesis for all tests indicates that the series has a unit root (non-stationary) in the level forms. We applied the Schwarz Information Criterion (SIC) to select the lag structure for the ADF and DF-GLS, while the bandwidth for the PP test was selected with the Newey-West Bartlett Kernel. The maximum lag length is chosen automatically as nine with SIC.

Table 2 on next page reports the unit root test results for the variables, together with the optimal lag lengths reported in the parentheses. The battery of unit root tests presented in the table almost unanimously indicates that all the variables are non-stationary in level and stationary in the first difference form. This indicates that the variables in the study are *I* (1).

As variables of the study are I(1), they can only be regressed in level if they are cointegrated. Otherwise, the results would be spurious, i.e. a significant relationship might be evident even though there is no true relationship exists. Cointegration theory suggests that a linear combination of two or more non-stationary series would be stationary (Engle & Granger 1987).

Table 2: ***Unit Root Test Results***

		ADF	DFGLS	PP	ADF	DFGLS	PP
			Levels			First difference	
Intercept	*cpc*	-2.24 (0)	0.39 (0)	-2.44	-6.87* (0)	-3.37* (0)	-6.87*
	ypc	-1.00 (0)	2.23 (0)	-1.00	-5.50* (0)	-5.55* (0)	-5.50*
	ypc^2	-0.84 (0)	2.34 (0)	-0.82	-5.54* (0)	-5.60* (0)	-5.54*
	T	-0.84 (0)	0.87 (0)	-1.51	-5.73* (1)	-0.99 (4)	-8.78*
	XC	-4.39* (0)	1.07 (1)	-7.59*	-8.08* (0)	-1.08 (2)	-7.73*
Intercept and trend	*cpc*	-1.67 (0)	-2.17 (0)	-1.61	-7.39* (0)	-7.36* (0)	-7.40*
	ypc	-2.03 (0)	-1.74 (0)	-2.14	-5.49* (0)	-5.61* (0)	-5.49*
	ypc^2	-1.97 (0)	-1.74 (0)	-2.10	-5.51* (0)	-5.63* (0)	-5.51*
	T	-2.76 (0)	-2.87 (0)	-2.70	-5.97* (1)	-6.31* (0)	-14.42*
	XC	-3.01 (0)	-1.18 (0)	-4.78*	-9.78* (0)	-4.02* (1)	-9.52*

*Note: * denotes significance at 1% critical levels.*

After identifying the degree of integration, we can now revolve to test for cointegration. ARDL bound testing approach to testing for cointegration requires the underlying regressors are purely I(0), purely I(1) or mutually cointegrated (Narayan & Narayan 2006), which conforms with our unit root test results. The estimation process with equation (2) requires selection of the optimal lags for the autoregressive part of the model at the early stage. The autoregressive part of the model incorporates lagged values of dependent variable and current and lagged values of the explanatory variables. The optimal lag length in the model is determined by general-to-specific modelling approach guided by the AIC criterion. The procedure involves testing whether shorter lags are feasible. Given the VAR based lag order selection presented in Table (3), a maximum lag of 3 has been chosen for each variable.

Given the information on the optimal lag structure of the autoregressive part of the model, we now check for the presence of long-run relationships in equation (2) by testing the joint significance of the estimated coefficients of lagged level variables. The calculated F-statistics Fc(Fcpc|ypc, ypc^2, T, *XC*) = 7.086, which is higher than the critical value (6.25 at k = 4 and n = 40) for the bound test at 1% level of significance provided by Narayan (2005). The calculated F statistics is higher than the upper bound critical value.

As mentioned above, the Johansen-Juselius cointegration test is also exploited to have a further robustness of the cointegration exercise. The test requires series to be I(1), which satisfies from the unit root test results presented in Table 2. However, before employing the cointegration test, it is necessary to run an unrestricted VAR (vector autoregression) to determine the maximum lag length because the Johansen-Juselius approach is sensitive to the lag length. A maximum lag length of 3 in the estimated VAR suggests that the residual in the model is out of any serial correlation. We then apply a number of lag length criterion, such as a LR test statistic (LR), a final prediction error (FPE), Akaike information criterion (AIC), Schwarz information criterion (SIC) and Hannan-Quinn information criterion (HQ) through the unrestricted VAR to determine the optimal lag length.

Table 3: ***Tests statistics and choice criteria for selecting lag order in the model***

Lag	LR	FPE	AIC	SC	HQ
0	NA	1.92e-13	-15.09258	-14.87930	-15.01606
1	314.1037	5.15e-17	-23.32882	-22.04916^	-22.86969
2	39.71752	4.80e-17	-23.46525	-21.11920	-22.62351
3	46.63464^	2.72e-17^	-24.21079^	-20.79836	-22.98644^

^ indicates lag order selected by the criterion

As can be seen in Table (3), only SC criterion suggests one as optimal lag length, other criterions supports three as maximum lag. Since consideration of a smaller lag length would create potential problems of serial correlation in the residual, we take 3 as an optimal lag. As the VAR was estimated in level form, we need to consider a maximum lag length 2 for the cointegration test. Given the visual plot of the data, we allow for linear deterministic trend in data but intercept (no trend) in cointegration test specification. The Johansen-Juselius cointegration test results are given in Table 4. As shown in the table, both trace and maximum eigenvalue statistics indicate the presence of one cointegrating equation at the 1% level.

Table 4: ***Johansen- Juselius Cointegration Test Results***

Trace				
Ho	Eigenvalue	Statistic	5% Critical Value	Prob.[a]
r = 0 †	0.73	99.75	69.82	0.00
r ≤ 1	0.42	48.63	47.86	0.04
r ≤ 2	0.34	27.26	29.80	0.09
Maximum Eigenvalue				
H_o	Eigenvalue	Statistic	5% Critical Value	Prob.[a]
r = 0 †	0.73	51.12	33.87	0.00
r ≤ 1	0.42	21.36	27.58	0.25
r ≤ 2	0.34	16.28	21.13	0.21

† denotes rejection of the hypothesis at the 1% level
[a] MacKinnon et al. (1999) p-values

Once the cointegration relationship among the variables is identified, equation (3) can be estimated to identify the long-run elasticity coefficients. Equation (3) is estimated as ARDL (0, 2, 0, 3), where the optimal order of lag is selected by the AIC criterion. The elasticity coefficients and test statistics are given in Table 5. The coefficient of *ypc* is not significant even though it comes with expected sign. Also, the long-run elasticity coefficient of *T* is highly insignificant with unexpected positive sign. This suggests that the state of technology as measured by multifactor productivity index placed insignificant role to curve CO_2 emissions in Australia during 1965-2006. Finally, we re-estimate long-run relationship in equation (3), excluding *T* from the model. The results are shown in Table 6.

Table 5: ***ARDL Model: Long-run relationship***

Equation (3): ARDL (0, 2, 0, 3) selected based on AIC. Dependent variable cpc_t			
Regressor	Coefficient	t-Statistics	Prob.
ypc_t	0.29	1.535	0.133
ypc_t^2	-0.23^{**}	-2.431	0.020
T_t	0.07	0.380	0.707
XC_t	0.07^{*}	2.729	0.009
Diagnostic test statistics	Test-stats	P-value	
Serial correlation	0.309	0.819	
ARCH	2.50	0.122	
Adj. R -squared	0.97		

Note: * and ** denote significance at 1% and 5% respectively.

Table 6: ***ARDL Model:Long-run relationship***

Equation (3) excluding *T*: ARDL (0,2,3) selected based on AIC. Dependent variable cpc_t			
Regressor	Coefficient	t-Statistics	Prob.
ypc_t	0.34^{**}	2.09	0.044
ypc_t^2	-0.23^{**}	-2.50	0.017
XC_t	0.07^{*}	3.32	0.002
Diagnostic test statistics	Test-stats	P-value	
Serial correlation	0.42	0.743	
ARCH	2.66	0.111	
Adj. R-squared	0.98		

Note: * and ** denote significance at 1% and 5% respectively.

slightly improve the explanatory power of the model. Estimated coefficient for *ypc* is significant at 5% level and implies that a 1 percent increase in per capita GDP will increase per capita CO_2 emissions by 0.34 percent in the long-run. The coefficient of ypc^2 is also significant at 5% level and poses the expected negative sign. The positive sign with *ypc* and negative sign with ypc^2 suggest the delinking of CO_2 emissions after a certain income level, supporting the existence of an inverted U-shaped relationship between per capita CO_2 emissions and per capita GDP in case of Australia. The EKC relationship of CO_2 emissions from the time series analyses in this research is similar to those of Halicioglu (2009) and Jalil and Mahmud (2009).

The coefficient of *XC* is highly significant and shows positive long-run elasticity. The elasticity coefficient is 0.07, attributing to the contribution of coal export to CO_2 emissions in Australia over the period of time. We apply Chow Breakpoint Test (Chow 1960) to investigate whether the oil crisis in mid-1970s led any structural break in the long-run parameters estimated in Table 6. The test statistics indicate no structural break in the estimated parameters due to the oil crisis. We also perform a number of diagnostic tests to validate standard assumptions. Serial correlation LM tests assert no serial correlation and ARCH test suggests acceptance of the null hypothesis of homoskedasticity (F-statistics 0.12, Probability 0.72). Cumulative sum of recursive residual (CUSUM) and sum of squares of recursive residual (CUSUM square) tests validate the parameter stability in the model. As can be seen in Figures 2 and 3, the plots of CUSUM and CUSUM square statistics are well within the critical bounds at 5 percent significance level.

Figure 2: ***Plot of cumulative sum of recursive residual***

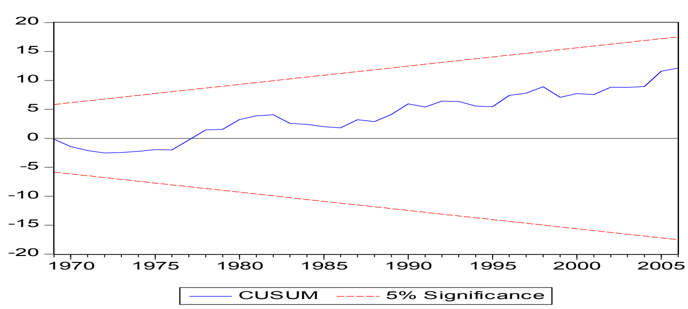
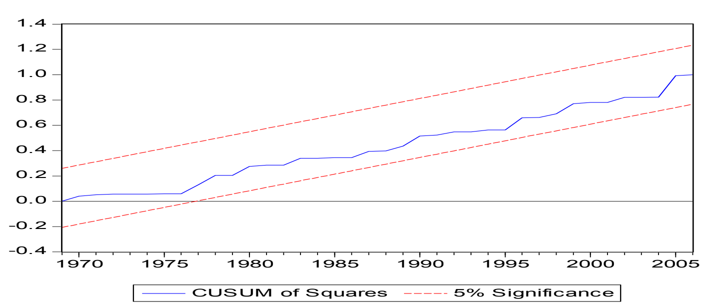


Figure 3: ***Plot of the sum of squares of recursive residual***



In order to investigate the short-term dynamics, the error correction representation in equation (4) is estimated. The results are presented in Table 7. As can be seen from the table, the short-run dynamic behaviour of the variables is consistent with long-run relationship found earlier. It is evident from panel A of the table that Δypc is significant, indicating a positive relationship in the short-run. However, Δypc^2, ΔXC and ΔT are not significant in the short-run relationship. Finally, we employ a regression by excluding T from equation (4) as the variable was found to be non-forcing in the long-run relationship. However, a re-estimation of the equation with remaining three variables led the residual to be heteroscedastic at 10 percent level. In such a situation, an OLS estimation provides a false sense of precision (Bollerslev 1986; Engle 1982). Therefore, we employ a standard GARCH (1, 1) model rather than an OLS to estimate the model, which is shown in panel B in table 7. The GARCH (1, 1) estimation turns Δypc, Δypc^2 and ΔXC as significant variables in the short-run relationship with consistent sign with long-run relationship. The sign and significance of the error correction terms confirm the existence of long-run relationship as revealed by both Johansen-Juselius test and ARDL bound testing approach of cointegration.

5. **Table 7: *ARDL Model: ECM estimates***

Dependent variable Δcpc_t						
Regressor	Panel A : ARDL (1,1,1,0) OLS estimation			Panel B : ARDL (1,1,3) GARCH (1, 1)		
	Coeff	t-Stats	Prob.	Coeff	z-Stats	Prob.
Δypc_t	2.07**	2.194	0.039	1.77*	2.763	0.006
Δypc_t^2	-0.76	-1.667	0.104	-0.76*	-2.881	0.004
ΔT_t	-0.28	-1.506	0.141	-	-	-
ΔXC_t	0.04	0.711	0.482	-0.08**	2.151	0.012
ecm(-1)	-0.33*	-3.487	0.001	-0.16**	-1.929	0.054
Diagnostic test statistics	Test-stats	P-value		Test-stats	P-value	
Serial correlation	0.82	0.612		-	-	
ARCH	1.10	0.30		0.134	0.716	

6. Note: * and ** denote significance at 1% and 5% respectively.

5. CONCLUSION AND POLICY IMPLICATION

This paper has investigated the relationship between CO_2 emissions and income in Australia, while controlling for multifactor productivity and export of black coal. Both long-run and short-run relationships have been investigated using data for a period of 1965-2006. The long-run cointegration relationship has been examined by using ARDL bound testing and Johansen-Juselius approaches. Both of the techniques suggest that cointegration relationship exists among the variables. The EKC hypothesis for per capita CO_2 emissions is tested by using an ARDL approach. The empirical results indicate a statistically significant EKC relationship for per capita CO_2 emissions in Australia. Export of black coal is found to play a significant role in CO_2 emissions in Australia in both short and long run. Australia is a global leader of coal trade and black coal represents largest commodity export, accounted for 23 per cent of total exports of goods and services in 2008-09.

In this paper, technological state is proxied by a multifactor productivity index. So far, empirical studies in this area of research have considered time trend to proxy technological state. However, as discoveries and diffusion of new technologies may not progress smoothly with time, the assumption of a deterministic technological progress may be incorrect in the long run. The use of multifactor productivity as a measure of technological state used in this paper, therefore, overcomes the limitations and provides practical policy directions. The empirical results for both long run and short run suggest insignificant role of technological improvement in reducing CO_2 emissions in Australia.

As multifactor productivity is found to play insignificant role, there could be other possible factors that can explain CO_2 emissions trajectory. Improvement for environmental awareness at higher income domain can be considered as a possible factor. Moreover, reduction in CO_2 emissions requires productivity growth to be accompanied by emissions specific changes (Stern 2004). These issues have not been explored in this paper. However, this paper draws an important lesson in that technological progress in Australia during 1965-2006 was not directed by CO_2 abatement policies. This further highlights a fundamental drawback with economic policies in Australia to encourage low carbon innovations. Australia, therefore, needs strong incentive mechanisms, such as an emission trading scheme or a carbon tax to provide necessary stimulus to markets to the development and adoption of low carbon technologies.

The study admits that the estimation of` multifactor productivity may reflect a host of measurement errors mainly related to price and quality changes, apart from measuring the effects of advances in the state of knowledge (Jorgenson & Griliches 1967). Another drawback of the measurement would be not to consider energy as an input factor along with capital and labour in the production function (Chen & Santos-Paulino 2010; Jorgenson 1984). Lipsey and Carlaw (2004) criticize the measure of multifactor productivity as the technological change, and suggests that it measures only the associated super normal returns to investing in such changes. As such, technological change can take place without changing the multifactor productivity. Therefore, a further decomposition of multifactor productivity to efficient improvement in an input of production, e.g., energy, would be required in this context. Again, energy consumption includes CO_2 intensive (e.g. coal) and non-CO_2 intensive (e.g. nuclear) energy sources. Exploring these decompositions of multifactor productivity and augmenting those in the emissions function is beyond the scope of this paper and remains open for future research. This paper, however, endeavours an important preliminary step to provide insights not only into the historical link between overall technological progress and CO_2 emissions but also into the way how the empirical research on technological progress in the context of achieving emissions reduction goals should be directed in the future.

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