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Analysis

CO_2 emissions, research and technology transfer in China

James B. Ang *

Department of Economics, Monash University, 900 Dandenong Road, Caulfield East, Vic 3145, Australia

A R T I C L E I N F O

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Although the economy of China has grown very strongly over the last few decades, this spectacular performance has come at the expense of rapid environmental deterioration. Amidst animated debate on the issue of global warming, this study attempts to explore the determinants of CO_2 emissions in China using aggregate data for more than half a century. Adopting an analytical framework that combines the environmental literature with modern endogenous growth theories, the results indicate that CO_2 emissions in China are negatively related to research intensity, technology transfer and the absorptive capacity of the economy to assimilate foreign technology. Our findings also indicate that more energy use, higher income and greater trade openness tend to cause more CO_2 emissions.

1. Introduction

The debate over global climate change has attracted copious attention from academic researchers and policy makers in recent years. As the major new global player, China's spectacular economic growth has been widely observed over the past few decades. Since the economic reforms of 1978, China has recorded an average real growth rate exceeding 9% a year. Per capita real income has increased almost tenfold during this period. Alongside this strong growth performance, there has been an associated rapid rise in energy consumption and pollution emissions. Energy use in China grew at an annual average rate of 7.2% during the period 1953–2006. Annual pollution emissions, measured by CO_2 in metric tons of carbon, increased from just 36.6 million in 1953 to 1625.7 million in 2006, representing a more than 40-fold increase.

In a recent study, Auffhammer and Carson (2008) highlight that the slowing of China's CO_2 per capita emissions growth rates, as previously predicted, is unlikely to materialize in the near future. In contrast, their forecasts suggest that China's CO_2 emissions are likely to increase dramatically over the short to medium term, and significantly exceed the amount required in the Kyoto Protocol. With rapid growth in pollution emissions, there has been increasing concern about their impact on China and the global economy. According to a recent study by Nielsen and Ho (2007), the aggregate national environmental health damage is estimated to be in the range of 3% to 7.7% of GDP. Moreover, The World Bank (2007) reports that the environmental pollution cost in China is estimated to be about 5.8% of its GDP.

While the importance of global warming issues is widely recognized among economists and policy makers, there has so far been little effort attempting to examine environmental performance in China, despite it currently being responsible for about one-fifth of global emissions. Most previous studies on this subject have focused on examining the future trends of energy consumption or CO_2 emissions in China (see, e.g., Chan and Lee, 1996; Sinton and Fridley, 2000; Crompton and Wu, 2005; Auffhammer and Carson, 2008). An important exception to this is the study by Cole et al. (2008), who focus on examining the determinants of environmental pollution for China using industry-level data for the period 1997–2003. Their results show that energy use and human capital have a positive impact on industrial pollution whereas productivity improvements and research activity tend to reduce emissions.

Our study differs from Cole et al. (2008) in several aspects. First, we utilize time series data for China going back as far as 1950. The use of a sufficiently long dataset enables us to analyze the long-run determinants of pollution as well as the short-run dynamics. Second, to the best of our knowledge, this is the first attempt that satisfactorily combines the environmental literature with modern endogenous growth theories. By doing so, it allows us to focus on the roles of R&D activity and technology transfer in reducing CO_2 emissions. This is done by incorporating factors that could induce higher productivity growth, as suggested by modern growth literature, into the pollution function. The rest of the paper is organized as follows. Section 2 sets

* Tel.: +61 3 99034516; fax: +61 3 99031128.
E-mail address: james.ang@buseco.monash.edu.au.

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out the analytical framework. Section 3 discusses construction of variables, data sources and the estimation techniques. Section 4 performs the empirical analysis and presents the results. The last section summarizes the results and concludes.

2. Theoretical framework

This section sets out the analytical framework underlying our empirical modeling strategy. Assuming a standard neoclassical production function with constant returns, we can write the aggregate output (y_t) function at time t as:

$$y_t = A_t f(K_t, L_t) \quad (1)$$

where A_t is total factor productivity (TFP), K_t is the capital stock and L_t is the number of workers. Bernard and Jones (1996a,b) assume that TFP growth (g_A) depends on technological catch-up so that:

$$g_A = \frac{\dot{A}_t}{A_t} = f(DTF_{t-1}) \quad (2)$$

where DTF_t is a variable measuring the technology gap between the frontier and the domestic economy (or distance to the frontier). The underlying principle in this simple model is that countries which are relatively backward can grow faster by utilizing technologies developed in the leading country. Therefore, a positive effect of DTF_t is expected due to the role of technology transfer in productivity growth. However, the above formulation of productivity catch-up is inadequate to explain the complex evolution of the growth rate in TFP. In this connection, we modify the above simple TFP growth specification in the following ways.

First, there is now an extensive literature on endogenous growth that emphasizes the importance of R&D efforts as an engine of growth. The key argument of the research-induced growth models is that TFP growth moves closely with R&D activity. For instance, the models of Romer (1990), Segerstrom et al. (1990), Grossman and Helpman (1991b) and Aghion and Howitt (1992)) suggest that the rate of productivity growth (g_A) depends on the growth rate of the R&D stock of knowledge:

$$g_A = \frac{\dot{A}_t}{A_t} = \rho \frac{\dot{SK}_t}{SK_t} \quad (3)$$

where SK_t is the stock of R&D knowledge. For low rates of depreciation of R&D stock, we can write the above as:

$$\dot{A}_t = \upsilon A_t \left(\frac{X}{Q}\right)_t \quad (4)$$

where X_t is R&D input and Q_t represents the variety of products in the economy. The ratio $(X/Q)_t$ is commonly referred to as research intensity. The above framework is in line with the Schumpeterian version of the R&D-based growth models of Aghion and Howitt (1998), Dinopoulos and Thompson (1998), Peretto (1998) and Howitt (1999). These models suggest the effectiveness of R&D is diluted due to the proliferation of products when an economy expands so that we can assume constant returns to the stock of R&D knowledge.

Second, there is a growing literature suggesting that domestic research activity plays a crucial role in facilitating the transfer of foreign technology (see Howitt, 2000; Griffith et al., 2003; Griffith et al., 2004; Cameron et al., 2005; Hu et al., 2005). For instance, using a general equilibrium model of endogenous growth, Griffith et al. (2003) combine the above two strands of literature and show that R&D, in addition to its direct effect, has an indirect effect on productivity growth that operates through the speed of technological catch-up. Specifically, a lagged interaction term between DTF_t and $(X/Q)_t$ is introduced to capture the second facet of R&D activity. It is postulated that the effect of R&D efforts on TFP growth will be greater for countries that lie further behind the technological frontier. As such, this interaction term, also known as the absorptive capacity, is expected to have a positive influence on TFP growth.

Third, recent studies have found that greater openness in the trade sector is positively associated with higher productivity growth-enhancing effects (see, e.g., Coe et al., 1997; Ades and Glaeser, 1999; Alesina et al., 2000; Choudhri and Hakura, 2000). In the models developed by Grossman and Helpman (1990, 1991a), trade openness affects firms' decisions to develop new products, which in turn depend on international competition and market size. Thus, international trade can promote more innovative activities in the domestic market and lead to higher productivity.

An augmented equation for TFP growth that incorporates these considerations can be given as follows:

$$g_A = \frac{\dot{A}_t}{A_t} = f\left[(X/Q)_{t-1},\ DTF_{t-1},\ (X/Q)_{t-1}\text{x}DTF_{t-1},\ TO_t\right] \quad (5)$$

The literature suggests that per capita energy use (E_t) and per capita real output (Y_t) are the key determinants of pollutant emissions (see, e.g., Liu, 2005; Ang, 2007). However, an unproductive economy can also generate more pollution. This is because a country which is more productive is able to use resources more efficiently (see Cole et al., 2005, 2008). In principle, higher productivity growth induced by technology transfer and more R&D efforts can improve environmental performance. This would be the case when a large proportion of the imported technology focuses on pollution abatement and R&D activities relate to the creation of clean technology that better protects the environment. Therefore, a more complete characterization of the pollution function should include productivity growth as a key determinant. Incorporating the role of TFP growth in abating pollution, we can write the environmental pollution function as:[1]

$$C_t = h\ [E_t,\ Y_t,\ f(g_A)] \quad (6)$$

Using the above TFP growth specification in Eq. (5), we can write the pollution equation as:

$$lnC_t = \alpha + \beta_1 \ln E_t + \beta_2 \ln Y_t + \beta_3 \ln TO_t + \beta_4 \ln(X/Q)_{t-1} \quad (7)$$
$$+ \beta_5 \ln DTF_{t-1} + \beta_6[\ln(X/Q)\text{x}\ln DTF]_{t-1} + \beta_7 Reg + \varepsilon_t$$

where C_t refers to an indicator of environmental quality for China (proxied by per capita CO_2 emissions), β's represent the long-run elasticities and ε_t is Gaussian errors. β_1 and β_2 are expected to be positive according to the literature. Greater trade openness is likely to result in more competition, causing the least productive and least energy-efficient firms to leave the market. However, Antweiler et al. (2001) and Cole and Elliott (2003), among others, postulate that the environmental impact of trade liberalization can be decomposed into scale (size of economy), technique (production methods) and composition (specialization) effects. While more pollution may occur due to the scale effect, the technique effect is likely to be beneficial to the environment. The composition effect depends on the country's comparative advantage. Hence, the net effect of free trade on the environment depends on the relative strength of each opposing force, and is therefore ultimately an empirical issue. Thus, the

[1] We have also attempted to model the pollution function using the environmental Kuznets curve (EKC) framework. The results are, however, less satisfactory. This is not surprising given that an EKC specification may not be appropriate for a developing country like China. In fact, previous studies by Ang (2007, 2008) have shown that such a specification is appropriate for France but not Malaysia. Moreover, Auffhammer and Carson (2008) show that an EKC specification for China yields sub-optimal forecast results. See also Wagner (2008) who show that the inverted U-shaped relationship found in the literature appears to be spurious and disappears once the observations have been appropriately de-factored.