CO2 Emissions, Research and Technology Transfer in China

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9 February 2009

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Abstract

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 nine percent 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 percent 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 forty-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 percent to 7.7 percent of GDP. Moreover, The World Bank (2007) reports that the environmental pollution cost in China is estimated to be about 5.8 percent 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 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:

$$y_t = A_t f(K_t, L_t) \tag{1}$$

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:

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

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:

$$g_A = \frac{\dot{A}_t}{A_t} = \rho \frac{\dot{SK}_t}{SK_t} \tag{3}$$

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:

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

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, 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:

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

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]

$$C_t = h\left[E_t,\ Y_t,\ f(\ g_A)\right] \tag{6}$$

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

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[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.

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

where C_t refers to an indicator of environmental quality for China (proxied by per capita CO_2 emissions), $\beta's$ 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 expected sign for β_3 is indeterminate. The expected signs for β_4, β_5 and β_6 are negative since R&D activity, technology gap and the absorptive capacity of technology transfer are expected to reduce pollution. Finally, following Cole *et al.* (2008), the empirical specification of the pollution function presented above also considers a legal dummy variable (*Reg*), which captures the effect of adoption of the Environmental Protection Law since 1979. Eq. (7) will be estimated using annual data for China over the period 1953-2006.

3. Data and Estimation Techniques

3.1 Measurement and data sources

This section describes the construction of variables, data sources and econometric techniques employed in the analysis. Long historical data on pollution for China are not available from any domestic official source. Therefore, we have obtained the data from an international source compiled by the Carbon Dioxide Information Analysis Center.[2] Following most prior studies (see, e.g., Holtz-Eakin and Selden, 1995; Friedl and Getzner, 2003; Martinez-Zarzoso and Bengochea-Morancho, 2004; Liu, 2005; Ang, 2007, 2008; Auffhammer and Carson, 2008), we consider per capita CO_2 emissions (C_t) as the measure for the level of pollution. It refers to the total emissions from fossil-fuel burning, cement manufacture and gas flaring. Data for other types of emissions going back as far as the 1950s are unfortunately not

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[2] The data are available for download at: http://cdiac.ornl.gov/ftp/trends/emissions/prc.dat.

available. Real GDP and energy consumption data are directly obtained from the China Statistical Yearbook. In line with CO_2 emissions, these two series are divided by population. We use the standard trade intensity measure, i.e., the sum of exports and imports over GDP, as the proxy for trade openness (TO_t).

In the literature, it is common to use either R&D labor or real R&D expenditure as the proxy for R&D input (X_t). However, data for R&D personnel are only available from 1978. The lack of R&D personnel data for the entire estimation period prompts us to consider using only R&D expenditure in the analysis. R&D expenditure, which is available continuously from 1953, is proxied by total scientific research expenditure. This is obtained from the National Bureau of Statistics of China (1999), and more recent data are taken from the China Statistical Yearbook. Largely due to the lack of R&D data for developing countries, almost all previous work on R&D-based growth models has focused only on OECD countries (see, e.g., Zachariadis, 2003; Guellec and De la Potterie, 2004; Ha and Howitt, 2007).

Distance to the frontier can be measured as follows:

$$DTF_t = \frac{A_t^L - A_t}{A_t^L} \tag{8}$$

where A_t^L is the level of total factor productivity of the technological leader at time t. Following the general practice in the literature, we take the United States as the technological frontier (see, e.g., Cameron *et al.*, 2005; Madsen *et al.*, 2008). The further China lies behind the technological leader, the larger the technology gap and therefore the greater the potential for technology transfer to benefit productivity growth and thereby reduce pollution.

Total factor productivity is computed as $Y_t / K_t^\pi L_t^{1-\pi}$. We use gross domestic product at constant price as the measure of real output (Y_t). Real capital stock (K_t) is computed using the perpetual inventory method (i.e., $K_t = I_t + (1-\delta)K_{t-1}$). In line with Coe and Helpman (1995), a depreciation rate (δ) of 5% and the growth rate of gross capital formation (g) at constant prices during the sample period, 1953-2006, are used to obtain the initial stock (K_0) for the year 1953, so that $K_0 = I_0 /(g+\delta)$, where I_0 is real gross capital formation in 1953. Following the established practice in the literature, capital's share of income (π) is set at 0.3. National account statistics for the U.S. are collected from the Bureau of Economic Analysis whereas labor data are taken from the Bureau of Labor Statistics. Data for Y_t, K_t and L_t for China covering the

period 1953-1999 are obtained from Wang and Yao (2003). We extend the data using more recent data points available from the China Statistical Yearbook.
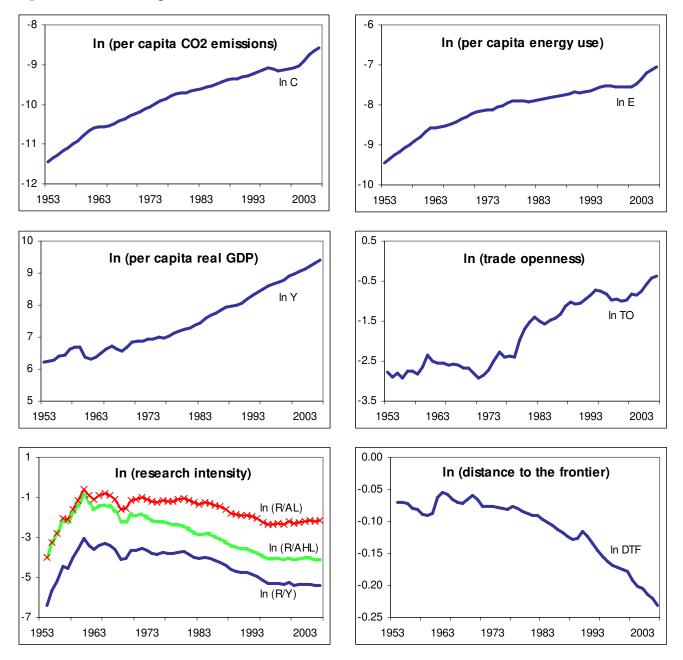
Figure 1: Time series plots of variables (1953-2006)

To measure R&D expenditure in real terms, we deflate by an unweighted average of a wage index and the GDP deflator. The former is constructed using data for average earnings of workers in urban units available from the China Statistical Yearbook. Data before 1978 are backdated by assuming that the growth rate of wages can be approximated by the sum of the rate of inflation and the growth rate in labor productivity (Y_t / L_t). Product variety (Q_t) is measured

by number of workers (L_t) and real output (Y_t). However, some adjustments for the measure of product variety are necessary given that there is a tendency for decreasing returns to R&D due to the increasing complexity of innovation (Ha and Howitt, 2007). Thus, labor is adjusted for productivity and human capital so that the following two additional measures of research intensity are also considered: $R_t / A_t L_t$ and $R_t / A_t H_t L_t$, where A_t is total factor productivity, and H_t is the stock of human capital, which is proxied by the average years of schooling. These additional measures therefore account for productivity or human capital adjustments or both. Data on human capital stock are obtained from Wang and Yao (2003) and extended accordingly using the methodology therein.[3]

The time series plots of the variables used in the empirical analysis are presented in Figure 1. It is evident that per capita CO_2 emissions (C_t), per capita energy use (E_t), per capita real output (Y_t) and trade openness (TO_t) all show a strong increasing trend over time. The measures of research intensity (R_t / Y_t, $R_t / A_t L_t$ and $R_t / A_t H_t L_t$) increase sharply during the 1950s and peak in the early 1960s. Since then, the series have been associated with a mild decreasing trend. The decline in the measure for distance to the frontier (DTF_t) indicates that the Chinese economy is catching up with the world technological leader.

3.2 Econometric Techniques

We adopt the traditional ARDL approach to the estimation of the long-run relationship and the short-run dynamics for environmental pollution and its determinants. Pesaran and Shin (1999) have shown that the OLS estimators of the short-run parameters are consistent, and the ARDL based estimators of the long-run coefficients are super-consistent in small sample sizes. Hence, valid inferences on the long-run parameters can be made using standard normal asymptotic theory. Moreover, this estimator is applicable irrespective of whether the regressors are $I(0)$ or $I(1)$. The optimal orders of the ARDL model are selected using the SIC by allowing for one lag in the estimation. In order to test the robustness of the results, all estimations are subject to various diagnostic tests. To provide for robustness checks, the environmental pollution equation is also estimated using three alternative single-equation estimators, namely the fully-modified OLS (FM-OLS) estimator of Phillips and Hansen (1990), the fully-modified unrestricted error-correction model (FM-UECM) of Inder (1993) and the dynamic ordinary least squares (DOLS) technique of Stock and Watson (1993).

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[3] These data are also available from Rawski and Perkins (2008).

Using the Wald tests, the resulting test statistics from the FM-OLS procedure are "fully-modified" by semiparametric corrections for serial correlation and for endogeneity. This "fully modified" procedure has been found to work well in finite samples, a feature which is particularly appealing given the small sample size used in the present study. In implementing the FM-UECM procedure, we follow Bewley (1979) by using the instrumental variable technique to correct the standard errors so that valid inferences can be drawn. Inder (1993) suggests that lagged level variables can be used as the instruments for the first-different current terms to correct for endogeneity bias. The key advantage of the DOLS procedure is that it allows for the presence of a mix of $I(0)$ and $I(1)$ variables in the cointegrated system. The estimation involves regressing one of the $I(1)$ variables on the remaining $I(1)$ variables, the $I(0)$ variables, leads (p) and lags ($-p$) of the first difference of the $I(1)$ variables, and a constant. By doing so, it corrects for potential endogeneity problems and small sample bias, and provides estimates of the cointegrating vector which are asymptotically efficient.[4]

4. Estimation Results

4.1 Long-run and short-run ARDL estimates

Table 1 presents the results for the pollution function estimated using the ARDL estimator. The table shows the results obtained for three models, where each model corresponds to the estimation results using different measures of research intensity. In view of sample size, we consider only one lag in the estimation. The choice of this lag length appears to be consistent with the optimal lag suggested by standard information criteria such as AIC and SBC.

It is evident that energy consumption enters the long-run pollution equation significantly at the one percent level with the expected sign. Specifically, the coefficients of $\ln E_t$ are found to be in the range of 1.073 to 1.104. Using the Wald tests, the null that the parameter of energy consumption is equal to one (or $H_0 : \beta_1 = 1$ in Eq. 7) cannot be rejected at the five percent significance level, suggesting that there is a one-to-one relationship between energy use and CO_2 emissions in China. The finding of a positive effect of energy use is consistent with Liu (2005) and Ang (2007, 2008), among others. The income variable ($\ln Y_t$), however, is found to have no statistically significant impact on the level of pollution, regardless of how research intensity is measured.

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[4] All underlying variables are found to be either $I(0)$ or $I(1)$, and this allows legitimate use of the ARDL and DOLS estimators. The unit root test results are not reported here to conserve space, but they are available upon request.

Trade openness ($\ln TO_t$) is found to have a positive impact on pollution, suggesting that a more liberalized trade sector tends to harm the environment. This finding is highly plausible for China given that the negative scale effect associated with trade liberalization on the environment is likely to outweigh the positive technique effect. Moreover, given China's status as a developing country, the pollution haven hypothesis suggests that its composition effect of trade is likely to degrade the environment. Hence, the overall effect of free trade on the environment is likely to be negative (see also Antweiler *et al.*, 2001; Cole and Elliott, 2003).

Turning to the measures of R&D intensity ($\ln(X/Q)_{t-1}$) and distance to the frontier ($\ln DTF_{t-1}$), the results strongly suggest that more R&D activity and the transfer of foreign technology are effective mechanisms for abating pollution. Our estimates show that research intensity has both direct and indirect effects on CO_2 emissions. Holding the indirect effect constant, the results show that research intensity is found to have a direct negative effect on CO_2 emissions in China, with a negative long-run elasticity in the range of 0.154 – 0.281. With regard to its indirect effect, the interaction term is found to be statistically significant and has the expected negative sign.

In this connection, it can be inferred that China's ability to assimilate foreign technical know-how can be enhanced through more R&D investment, and this highlights the important role of local R&D capability as an effective channel for tapping into technology developed in the frontier countries (see Hu *et al.*, 2005). This interpretation is obvious when we obtain the derivative of $\ln C_t$ with respect to $\ln(X/Q)_{t-1}$. In Model A, this gives $-0.179 - 1.767 \ln(X/Q)_{t-1}$. Our results imply that more R&D spending will result in lower pollution via two channels: 1) directly mitigating the environmental damage by facilitating the innovation of new production techniques that help abate pollutant emissions; and 2) enabling firms to more effectively assimilate green technology developed elsewhere, thus helping narrow the technology gap between the frontier and the domestic economy. With regard to the direct effect of distance to the frontier, a one percent increase in the technology gap tends to reduce pollution by 5.639 to 9.720 percent, holding research intensity constant. This finding suggests that China can gain significant benefits by using technology developed elsewhere to help combat pollution. The coefficients associated with *Reg* are found to be negative and significant in all models. Thus, environmental regulation appears to be an effective device in containing CO_2 emissions.

Table 1: ARDL estimates of the CO_2 emissions equation (1953-2006)

	Model A $(X/Q)_t = (R/Y)_t$		Model B $(X/Q)_t = (R/AL)_t$		Model C $(X/Q)_t = (R/AHL)_t$	
	Coeff.	*p*-value	Coeff.	*p*-value	Coeff.	*p*-value
I. The long-run relationship ($Dep. = \ln C_t$)						
Intercept	-2.206***	0.000	-2.327**	0.013	-2.055***	0.000
$\ln E_t$	1.104***	0.000	1.081***	0.000	1.073***	0.000
$\ln Y_t$	0.008	0.889	0.057	0.484	0.012	0.820
$\ln TO_t$	0.128***	0.000	0.138***	0.002	0.140***	0.000
$\ln(X/Q)_{t-1}$	-0.179***	0.000	-0.281***	0.001	-0.154***	0.000
$\ln DTF_{t-1}$	-9.720***	0.000	-6.989**	0.010	-5.639***	0.000
$\ln(X/Q)_{t-1}$ x $\ln DTF_{t-1}$	-1.767***	0.000	-3.186***	0.001	-1.381***	0.000
Reg	-0.083**	0.024	-0.118*	0.053	-0.092***	0.008
II. The short-run dynamics ($Dep. = \Delta \ln C_t$)						
Intercept	-1.197***	0.003	-0.800*	0.053	-1.166***	0.002
ECT_{t-1}	-0.545***	0.000	-0.344***	0.001	-0.567***	0.000
$\Delta \ln E_t$	0.601***	0.000	0.617***	0.000	0.609***	0.000
$\Delta \ln Y_t$	0.004	0.890	0.020	0.508	0.007	0.822
$\Delta \ln TO_t$	0.070***	0.000	0.047**	0.015	0.080***	0.000
$\Delta \ln(X/Q)_{t-1}$	-0.097***	0.000	-0.097***	0.000	-0.087***	0.000
$\Delta \ln DTF_{t-1}$	-5.293***	0.000	-2.404***	0.001	-3.200***	0.000
$\Delta[\ln(X/Q) \times \ln DTF]_{t-1}$	-0.962***	0.000	-1.096***	0.000	-0.784***	0.000
ΔReg	-0.045**	0.013	-0.040**	0.036	-0.052***	0.003
III. Diagnostic checks	Test-stat.	*p*-value	Test-stat.	*p*-value	Test-stat.	*p*-value
χ^2_{SERIAL}	1.028	0.311	1.205	0.272	1.613	0.204
χ^2_{WHITE}	3.732	0.881	3.736	0.880	4.177	0.841
χ^2_{ARCH}	0.208	0.649	0.293	0.588	0.203	0.652
χ^2_{RESET}	0.256	0.613	0.159	0.690	0.672	0.413

Notes: χ^2_{NORMAL} refers to the Jarque-Bera statistic of the test for normal residuals, χ^2_{SERIAL} is Breusch-Godfrey LM test statistics for no first-order serial correlation, respectively, χ^2_{WHITE} denotes the White's test statistic to test for homoskedastic errors, χ^2_{ARCH} is the Engle's test statistic for no autoregressive conditional heteroskedasticity and χ^2_{RESET} is the Ramsey's test statistic for no functional misspecification. *, ** and *** indicate 10%, 5% and 1% levels of significance, respectively.

The short-run dynamics of the CO_2 emissions function are reported in panel II of Table 1. Similar to the long-run results, income growth is found to have no statistically significant impact on the increase in pollution. In first-differenced form, the variables have expected signs, consistent with the results obtained for the long-run models. The magnitudes of all the coefficients are smaller than their long-run counterparts, suggesting that these variables have stronger effects on pollution in the long run. For instance, in Model A, a one unit increase in research intensity is associated with a 0.179 unit reduction in pollution in the long run. However, in the short run, a one percentage point increase in the growth rate of research intensity is correlated with only a 0.097 percentage point decrease in the growth rate of CO_2 emissions.

The error-correction term (ECT) captures the evolution process on the variable of concern, in this case $\Delta \ln E_t$, by which agents adjust for prediction errors made in the last period. The coefficients on ECT_{t-1}, which measure the speed of adjustment back to the long-run equilibrium value, are statistically significant at the one percent level and correctly signed, i.e., negative. This implies that an error-correction mechanism exists in the CO_2 emissions function so that the deviation from long-run equilibrium has a significant impact on the growth rate of pollution. This provides some evidence supporting the presence of the underlying relationship in the long run. It is found that the economy will adjust at a speed of 34.4 percent to 56.7 percent a year to restore equilibrium when there is a shock to the steady-state relationship.

4.2 Robustness checks

The results reported in panel III of Table 1 show that the regression specifications fit remarkably well. In particular, in all models, we do not find any evidence of serial correlation, heteroskedasticity, autoregressive conditional heteroskedasticity and functional misspecification at the conventional levels of significance. The structural stability of the emissions function is examined using the cumulative sum (CUSUM) tests on the recursive residuals.[5] The test is able to detect systematic changes in the regression coefficients. Figure 2 shows that the statistics generally lie within or on the five percent confidence interval bands, suggesting no structural instability in the residuals of the emissions equation.

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[5] We have also tested for the presence of structural breaks by interacting all variables (except trade openness) in the equation with a dummy variable (*d*) to capture the effects of the reforms that took place since 1978. *d* equals 1 for the post-reform period and is set to zero before the reform. The reform date is alternatively assumed to be 1978, 1980 and 1982. With no exception, all these interaction terms turn out to be statistically insignificant, providing some support that our results are not distorted by the regime shifts that have occurred following the reform episode.
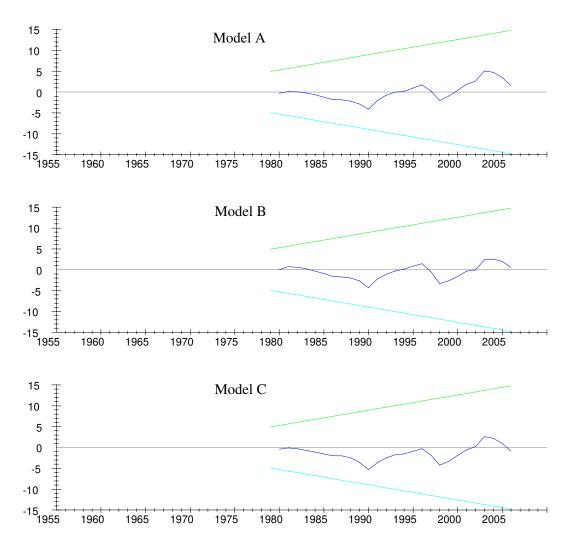
Figure 2: Plots of cumulative sum of recursive residuals

Model A

Model B

Model C

Notes: The straight lines represent critical bounds at the 5% significance level.

4.3 Alternative estimators

The sensitivity of the results is further assessed using three other estimators, namely the FM-OLS procedure of Phillips and Hansen (1990), the FM-UECM estimator of Inder (1993) and the DOLS procedure of Stock and Watson (1993). As Table 2 shows, these approaches give very similar results compared to those estimated using the ARDL approach. Although the magnitude of the coefficients shows some small variations, the qualitative aspects of the results are, by and large, consistent with those obtained using the ARDL estimator. An exception is that income is found to have a statistically positive effect on pollution when the models are estimated using the approaches that involve a fully-modified procedure. Importantly, the key findings that research intensity, distance to the frontier and their interaction help reduce CO_2 emissions remain unaltered. The results are insensitive to choice of the research intensity measures. The

short-run results and diagnostic tests are also similar to those obtained using the ARDL estimation technique, and hence not reported here for brevity. We therefore conclude that the results are quite robust overall to the choice of estimators.

Table 2: Alternative estimates for the CO_2 emissions equation (1953-2006)

	Model A $(X/Q)_t = (R/Y)_t$		Model B $(X/Q)_t = (R/AL)_t$		Model C $(X/Q)_t = (R/AHL)_t$	
I. FM- OLS	Coeff.	*p*-value	Coeff.	*p*-value	Coeff.	*p*-value
Intercept	-2.800***	0.000	-2.925***	0.000	-2.641***	0.000
$\ln E_t$	1.076***	0.000	1.048***	0.000	1.054***	0.000
$\ln Y_t$	0.098**	0.019	0.150***	0.002	0.091**	0.024
$\ln TO_t$	0.109***	0.000	0.112***	0.000	0.118***	0.000
$\ln(X/Q)_{t-1}$	-0.133***	0.000	-0.133***	0.000	-0.121***	0.000
$\ln DTF_{t-1}$	-5.770***	0.000	-1.245	0.193	-3.060***	0.001
$\ln(X/Q)_{t-1} \times \ln DTF_{t-1}$	-1.285***	0.000	-1.337***	0.001	-1.038***	0.000
Reg	-0.037	0.153	-0.029	0.318	-0.049**	0.046
II. FM-UECM						
Intercept	-2.699***	0.000	-2.775***	0.000	-2.478***	0.000
$\ln E_t$	1.088***	0.000	1.064***	0.000	1.067***	0.000
$\ln Y_t$	0.094***	0.000	0.141***	0.000	0.077***	0.000
$\ln TO_t$	0.097***	0.000	0.099***	0.000	0.106***	0.000
$\ln(X/Q)_{t-1}$	-0.130***	0.000	-0.131***	0.000	-0.122***	0.000
$\ln DTF_{t-1}$	-5.634***	0.000	-1.196***	0.000	-3.045***	0.000
$\ln(X/Q)_{t-1} \times \ln DTF_{t-1}$	-1.247***	0.000	-1.267***	0.000	-0.993***	0.000
Reg	-0.026*	0.073	-0.016	0.279	-0.036**	0.012
III. DOLS						
Intercept	-0.912	0.322	-1.879*	0.096	-1.090	0.166
$\ln E_t$	1.175***	0.000	1.101***	0.000	1.128***	0.000
$\ln Y_t$	-0.121	0.216	0.032	0.756	-0.081	0.325
$\ln TO_t$	0.153***	0.000	0.144***	0.001	0.160***	0.000
$\ln(X/Q)_{t-1}$	-0.193***	0.000	-0.201***	0.001	-0.162***	0.000
$\ln DTF_{t-1}$	-12.295***	0.000	-5.001**	0.028	-7.541***	0.000
$\ln(X/Q)_{t-1} \times \ln DTF_{t-1}$	-1.978***	0.000	-2.273***	0.001	-1.592***	0.000
Reg	-0.079***	0.006	-0.075**	0.027	-0.084***	0.002

Notes: the short-run dynamics and the diagnostic test results are not reported to conserve space. They are available upon request. *, ** and *** indicate 10%, 5% and 1% levels of significance, respectively.

4.3 Alternative specification

Our underlying model assumes so far that all the right-hand-side variables in Eq. (7) have a direct effect on CO_2 emissions. However, the model may be misspecified since some of these variables may act indirectly on CO_2 emissions through the channel of energy demand rather than operating directly on CO_2 emissions once we control for energy demand. In light of this, we also estimate a simultaneous equation system to further examine the robustness of the results.[6] For the first equation, we assume that per capita pollutant emission (C_t) is a function of per capita energy consumption (E_t), trade openness (TO_t), research intensity [$(X/Q)_t$] and a dummy variable capturing the effect of environmental regulation (*Reg*), as follows:

$$\ln C_t = \chi_0 + \chi_1 \ln E_t + \chi_2 \ln TO_t + \chi_3 \ln(X/Q)_{t-1} + \chi_4 Reg + \mu_t \tag{9}$$

The second equation, i.e., the energy demand function, is postulated to take the form of Eq. (10). Here, per capita energy consumption (E_t) is specified as a function of per capita real income (Y_t), distance to the frontier (DTF_t) and absorptive capacity [$(X/Q)_{t-1}$ x DTF_{t-1}], as follows:[7]

$$\ln E_t = \delta_0 + \delta_1 \ln Y + \delta_2 \ln DTF_{t-1} + \delta_3 [\ln(X/Q) \text{x} \ln DTF]_{t-1} + v_t \tag{10}$$

Under this simultaneous framework, we assume that more R&D investment encourages the innovation of new production techniques or green technology that helps curb CO_2 emissions, and hence χ_3 is expected to be negative. Both technological backwardness and absorptive capacity of the domestic economy enables the adoption of energy-efficient technology developed by the frontier countries, and this effectively reduces energy consumption. Thus, both δ_2 and δ_3 are expected to carry a negative sign.

Eqs. (9) and (10) are jointly estimated using the seemingly unrelated regression (SUR) (or Zeller's method) and the full information maximum likelihood (FIML) estimators to obtain the parameter estimates of the system. The former accounts for both heteroskedasticity and

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[6] We thank an anonymous referee for drawing our attention to this point and for recommending this alternative modelling approach.

[7] We have also considered research intensity in the energy demand equation due to Fisher-Vanden *et al.* (2004) and Fisher-Vanden and Jefferson (2008). However, the inclusion of this variable gives unsatisfactory regression results and therefore it is omitted in the specification.

contemporaneous correlation in the residuals across all equations whereas the latter is a fully efficient estimator which assumes that the contemporaneous errors have a joint normal distribution. The estimates reported in Table 3 show that our earlier results are, by and large, insensitive to this alternative modelling framework. Although the legal dummy and distance to the frontier become insignificant in some cases, all variables continue to have their expected signs and are highly significant. The system estimates are also robust to different measures of research intensity and the choice of estimators.

Table 3: SUR and FIML estimates for the simultaneous equation system

	Model A $(X/Q)_t = (R/Y)_t$		Model B $(X/Q)_t = (R/AL)_t$		Model C $(X/Q)_t = (R/AHL)_t$	
	SUR	FIML	SUR	FIML	SUR	FIML
I. The Emissions Function (Dep. = $\ln C_t$)						
Intercept	-1.228*** (0.000)	-1.095*** (0.000)	-1.101*** (0.000)	-0.985*** (0.000)	-1.329*** (0.000)	-1.239*** (0.000)
$\ln E_t$	1.128*** (0.000)	1.152*** (0.000)	1.134*** (0.000)	1.153*** (0.000)	1.115*** (0.000)	1.130*** (0.000)
$\ln TO_t$	0.127*** (0.000)	0.112*** (0.000)	0.131*** (0.000)	0.119*** (0.000)	0.113*** (0.000)	0.103*** (0.000)
$\ln(X/Q)_{t-1}$	-0.031*** (0.000)	-0.035*** (0.003)	-0.035*** (0.000)	-0.040*** (0.006)	-0.040*** (0.000)	-0.043*** (0.002)
Reg	-0.152** (0.041)	-0.107 (0.245)	-0.128* (0.052)	-0.101 (0.232)	-0.081 (0.317)	-0.048 (0.678)
II. The Energy Demand Function (Dep. = $\ln E_t$)						
Intercept	-14.326*** (0.000)	-14.237*** (0.000)	-13.769*** (0.000)	-13.747*** (0.000)	-15.651*** (0.000)	-15.571*** (0.000)
$\ln Y_t$	0.971*** (0.000)	0.962*** (0.000)	0.905*** (0.000)	0.905*** (0.000)	1.181*** (0.000)	1.170*** (0.000)
$\ln DTF_{t-1}$	-10.792*** (0.000)	-10.167*** (0.009)	-1.572 (0.365)	-1.124 (0.677)	-3.466 (0.178)	-3.443 (0.282)
$\ln(X/Q)_{t-1} \times \ln DTF_{t-1}$	-3.219*** (0.000)	-3.171*** (0.000)	-3.464*** (0.000)	-3.424*** (0.000)	-3.284*** (0.000)	-3.310*** (0.000)

Notes: Figures in parenthesis indicate the *p*-values. *, ** and *** indicate 10%, 5% and 1% levels of significance, respectively.

5. Summary and Conclusions

This study was motivated by the observation of a rapid deterioration in the environmental quality of China in recent years along with its strong growth performance, and the lack of any previous attempts to analyze the underlying forces influencing CO_2 emissions at

the aggregate level. Amidst active debate on global warming issues, the present study provides timely information to guide policy formulation for China as well as other developing countries.

The analytical framework combines modern growth theoretical underpinnings with the environmental literature so that we can focus the analysis on the roles of R&D activity and technology transfer in reducing pollution. Using aggregate data for China for more than half a century, the empirical results show that an increase in energy use and trade intensity contribute to higher CO_2 emissions in China. On the other hand, CO_2 emissions decrease with increases in research activity, distance to the technological frontier and their interaction that reflects the ability of China to absorb foreign technology. Given the significant interaction between R&D intensity and the technology gap, increased domestic R&D activity will help the domestic economy to assimilate technology developed in the leading countries more effectively. Thus, research intensity exerts both direct and indirect beneficial influences in abating CO_2 emissions. There is also some evidence that higher aggregate demand induces more CO_2 emissions but the adoption of more stringent environmental regulations helps in abating them.

However, it should be highlighted that since the estimation results are based on time series aggregate data, our estimates may not be consistent with analysis conducted at the provincial level, which provides more degrees of freedom in estimation but involves a much shorter time horizon. The use of provincial data is beyond the scope of the present paper and will be left for future research. Notwithstanding this limitation, the findings of this paper are broadly in line with the literature and have important implications for policy design. To the extent that research intensity and its interaction with distance to the frontier technology have a positive effect in reducing CO_2 emissions, policies that encourage more research activity will not only help contain pollution directly through facilitating more innovation in production techniques that emit less pollutions, but will also enable China to more effectively absorb technology developed elsewhere and thereby catch up to the frontier's green technology. Thus, increasing research efforts have dual positive effects in containing pollution. These effects are expected to continue given that China is unlikely to surpass the world technological leader in the near future. Finally, the results in this study also highlight that modern R&D-based endogenous growth models can be applied to understand issues related to environmental pollution even in the context of developing economies.

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