The effect of human capital on CO_2 emissions: Macro evidence from China

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ABSTRACT

We study the effect of human capital on CO_2 emissions using the Chinese provincial panel over the period 1997–2016. Allowing for cross-sectional dependence and structural breaks, we find a negative association between human capital and CO_2 emissions in the long run and attribute it to the influences from younger workers and workers with advanced human capital. In particular, our results suggest that a one-year increase in average schooling reduces CO_2 emissions by 12 per cent. Using disaggregated emission dataset by energy sources and end emitters, we demonstrate this negative association is likely to manifest through technology effect and the improvement in energy efficiency. These manifestations are limited to production sector. Our finding suggests a promising avenue for abating greenhouse gases without impeding economic growth.

Keywords: human capital, CO_2 emissions, climate change; China; panel model.
JEL Codes: C33, Q43, J24, O5

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1. INTRODUCTION

Investing in human capital has been shown to generate various benefits. For instance, human capital is conducive to labor productivity and facilitates economic growth (Schultz, 1961; Romer, 1990; Barro, 1991). It is also associated with many social externalities such as better health and lower crime participation, to name a few (see the survey of Sianesi and van Reenen, 2003). Yet, while these externalities have sparked growing attentions, the environmental benefits owing to human capital accumulation remains less understood.

We attempt to fill this gap by studying the association between human capital and carbon dioxide (CO_2) emissions for a panel of Chinese provinces over the period 1997–2016. China is an appealing context as it pledges to cut CO_2 emissions ambitiously in the Paris Agreement and has been investing education rigorously since the 1990s (Naughton, 2007; UNFCCC, 2017).[1]

Empirically, we estimate the long-run relationship between human capital and CO_2 emissions. Our results suggest that human capital embodied in younger workers and workers with advanced human capital exerts a negative and significant effect on CO_2 emissions. Our results, which account for cross-sectional dependence and structural breaks, reveal that a one-year increase in average schooling reduces CO_2 emissions by 12 per cent. This result is driven by younger workers aged between 25 to 44 years old in which their one more schooling year is associated with 26.8 per cent lower CO_2 emissions. While these figures may appear large, our dataset demonstrates that it takes about ten years of efforts for China to attain one extra year of formal schooling.[2] On another metric of human capital, we find that a one per cent increase in advanced human capital, which is proxied by the share of workers with a tertiary qualification, reduces CO_2 emissions by 5.7 per cent.

Our study relates and contributes to at least three strands of literature. The first strand is a set of emerging studies that address the nexus between human capital and energy consumption at the macro level (Salim et al., 2017; Shahbaz et al., 2019; Yao et al., 2019). These studies have consistently revealed a negative human capital–energy consumption association at either regional or country levels. Specifically, Yao et al. (2019) analyzed a panel of OECD economies over the period 1965–2014 and added that human capital reduces dirty energy consumption but increases clean energy consumption. This novel finding suggests that human capital accumulation may improve environmental quality through switching away from fossil fuel which is a primary cause of CO_2 emissions.

The second strand of related literature is constituted of several firm-level studies that attempt to understand whether and how human capital reshapes firms' polluting behaviors (Blackman and Kildegaard, 2010; Gangadharan, 2006; Lan and Munro, 2013; Cole et al., 2008). These studies generally reported a positive nexus between human

[1] Under the recent Paris Agreement, China has pledged to cut carbon intensity by 60 to 65 per cent from the 2005 level before 2030 (UNFCCC, 2017). Using World Development dataset, we show this is a challenge task. Over the period 2000–2015, the carbon intensity decreases at annual rate of 1.49 per cent on average. However, to meet the lower bound of the target (60 per cent reduction from the 2005 level), carbon intensity must decrease at the rate of 4.2 per cent annually from 2016 onward. Assuming the pre-2014 trend maintains, it means China needs to come up a way to lower carbon intensity growth by another three percentage points. When the upper bound target (65 per cent reduction) is pursed, the task becomes more pressing.

[2] See the report of China Center for Human Capital and Labor Market Research (CHLR) retrieved from http://humancapital.cufe.edu.cn/en/Human_Capital_Index_Project.htm

capital and environmental outcomes. A consensus of the underlying mechanisms is that firms with a higher stock of human capital are more likely to exhibit better environmental compliance and adopt cleaner production technology.

The third set of studies, which are most closely related to ours, is an embryonic, and predominantly very recent, literature has directly associated human capital and several pollutants, including CO_2 emissions. Using a cross-sectional dataset of the U.S. states, Goetz et al (1998) documented that, conditional on income, population density and industrial composition, the states with better educated population appear to have cleaner ambient environment. Using the time series observations between 1978 and 2018 from China, Li and Ouyang (2019) found that human capital promotes CO_2 emissions in the short run but reduces it in the long run. To address the potential nonlinear relationship between human capital and CO_2 emissions, Yao et al. (2020) assembled a historical OECD panel over the period 1870–2014, finding that human capital started to alleviate carbon emissions since the 1960s.

We build, and improve, especially on this third set of studies in several important manners. Each of these studies provides estimates using either time series or cross-country dataset. We employ a panel of Chinese provinces over the period 1997–2016, which constitutes a more homogeneous panel. Our sample thus diminishes the unobserved differences that often plague cross-country studies (Madsen et al., 2018). Meanwhile, the context of China offers a unique advantage to our estimation. Exposure to pollution is believed to be endogenous as better educated cohorts may sort into regions with better environmental quality (Neidell, 2009; Graff Zivin and Neidell, 2012). While this self-selection process could be addressed through instrumental variable (IV), finding valid IV for human capital at the provincial level is notoriously difficult in a panel framework (Fleisher et al., 2010). Our panel largely exempts from this challenge as *Hukou* policy makes the internal migration, which could be induced by pollution, extremely costly.[3]

Another innovation of our study is that we not only examine the association between the overall level of human capital, proxied by the number of total schooling years, and CO_2 emissions, but also consider its distribution across different age cohorts. This strategy enables us to understand the underlying mechanisms through which human capital may affect CO_2 emissions. Moreover, to capture the heterogeneous effects of human capital on CO_2 emissions, we also break qualification, which is another proxy of human capital, into secondary and tertiary levels.[4] This distinction is important because advanced human capital, usually obtained from tertiary education, is unlikely to exert the same effect on the environmental quality as basic human capital obtained from primary and secondary educations (Gemmell, 1996). The underlying explanation is that production-relevant skills are embodied in those individuals who have acquired advanced qualifications. Specifically, more educated workers imply that the cost of complying with more stringent environmental standards, such as through adopting cleaner production technologies, will be lower (Dasgupta et al., 2000; Lan and Munro, 2013; Yao et al., 2020).

[3] *Hukou* policy is officially called household registration system, which ties one's accession to social welfare, like highly-subsidized education and medication, to his or her birth place. Although the stringency of *Hukou* has been relaxed over recent years, barriers to inter-provincial, permanent, migration remain prohibitively high (See Yao et al. 2018 for a detailed discussion). We acknowledge that China remains a developing country and an overwhelmingly share of migrant workers is motivated by economic opportunities rather than pursing better environment. To formally address this endogeneity issue, we have considered internal instruments and performed heterogeneous Granger causality test in sensitivity check section.

[4] We do not consider primary education as the variations of it are small throughout our sample period, possible due to radical implementation of Nine-Year Compulsory Education program since 1980s.

Our final contribution rests on investigating the mechanisms underlying the established human capital–CO_2 emissions nexus. While it is challenging at the macro level, we take the advantage of disaggregated emissions by energy sources and end emitters. Specifically, to examine whether technology effect attributed to human capital accumulation is at play, we use industrial CO_2 emissions due to cement production process. Since the process emissions, by definition, have fully excluded the CO_2 emissions accrued to energy consumption, the negative effect exerted by human capital could only be operating through technology effect (e.g. more environmentally-friendly production process).

Our findings offer new insights to the policy circle. To date, conventional solutions like command-and-control remain the fundamental tools for the Chinese government to control pollution. The outcomes, however, are achieved at the expense of substantial welfare loss (Zhang, 2017). Given China is an authoritarian state still riddled with red tape, the efficiency and effectiveness of those regulation-based tools are further constrained (Wang and Wheeler, 2005; Dean et al., 2009). The market-based policy instruments are expected to fill the void. However, available instruments like carbon tax and emission trading scheme (ETS) are still at an early stage and yet to be fully implemented, making their efforts on abating CO_2 emissions marginal at best. With this backdrop, we suggest investing in human capital could be used to facilitate carbon reduction and to control other pollutions without distorting economic growth much. We do recognize that human capital accumulation is neither the necessarily only, nor the most important way for abating CO_2 emissions. Nevertheless, we believe this study improves our understanding of social benefits associated with human capital accumulation, extending them to the perspective of environmental protection.

The rest of this paper is organized as follows: Section 2 setups conceptual framework which guides our empirical investigation. Section 3 explains the dataset and econometric methods. Section 4 presents baseline results and section 5 performs sensitivity checks. We attempt to identify the potential mechanisms in section 6. The last section concludes and discusses policy implications.

2. CONCEPTUAL FRAMEWORK AND EMPIRICAL MODEL

2.1 Conceptual framework

To explore the association between human capital and CO_2 emissions, we discuss the potential channels accrued to production and household sectors separately.[5]

In the production sector, human capital accumulation is expected to promote environmental quality because better-educated workers are conducive to both innovation and the diffusion of abatement technologies (Blackman and Kildegaard, 2010; Lan and Munro, 2013). Specifically, firms with higher human capital tend to be long-run oriented, emphasizing their sustainable development by exercising more stringent pollution controls. On the other hand, firms

[5] The conceptual discussion is similar to our preceding study using historical OECD panel (see Yao et al., 2020). To differ from that study, apart from using different dataset, we also construct a theoretical model that formally predicts the negative association between human capital and environmental quality.

managed by better-educated professionals tend to follow higher standards of social responsibility, making them less likely to violate external environmental regulations (Dasgupta et al., 2000; Gangadharan, 2006; Blackman and Kildegaard, 2010; Lan and Munro, 2013).

In the household sector, better educated families tend to value the environment more and modify their behavior in ways that alleviate environmental impacts, such as greater use of recycling (Goetz et al., 1998; ESRC, 2011). For instance, a survey of British households revealed that households with tertiary qualifications are 25 per cent more likely to adopt an environmentally-friendly lifestyle than those without such qualifications (ESRC, 2011). Meanwhile, both Broadstock et al. (2016) and Pachauri and Jiang (2008) observed that households with higher human capital are more likely to select appliances which are more energy efficient. Communities with higher human capital have also been more successful in organizing opposition to local polluters. Pargal and Wheeler (1996), for instance, found that in Indonesia, collective bargaining against water polluters was stronger in better-educated communities.

In light of the above discussion, we formalize a theoretical model based on Graff Zivin and Neidell (2013).[6] For a given level of production and consumption in an economy, we start with the pollution function below:

$$E = f(M(A), A(HC, E_S), I_0)$$

where E is the pollution level; M refers to the mitigation effort, which is a function of environmental awareness A. Meanwhile, A is a function of E_S and HC. E_S captures the environmental signals like deteriorating air quality or serious environmental accidents; HC is the level of human capital. I_0 is the reference pollution level for the given level of production and consumption.

This pollution function states that how human capital affects pollution without changing the level of production and consumption of an economy. It shows that human capital HC and environmental signals E_S are two components determining the environmental awareness of firms and households, which, in turn, affect their mitigation efforts against pollution.

The qualitative relationship between human capital and pollution can be solved by taking the full derivative of the pollution function with respect to HC, yielding the following results:

$$\frac{dE}{dHC} = \underbrace{\left(\frac{\partial E}{\partial M} * \frac{\partial M}{\partial A} + \frac{\partial E}{\partial A}\right)}_{\frac{dE}{dA}} * \underbrace{\left(\frac{\partial A}{\partial HC} + \frac{\partial A}{\partial E_S} * \frac{\partial E_S}{\partial HC}\right)}_{\frac{dA}{dHC}}$$

Mathematically, $\left(\frac{\partial E}{\partial M} * \frac{\partial M}{\partial A} + \frac{\partial E}{\partial A}\right)$ and $\left(\frac{\partial A}{\partial HC} + \frac{\partial A}{\partial E_S} * \frac{\partial E_S}{\partial HC}\right)$ collapse to $\frac{dE}{dA}$ and $\frac{dA}{dHC}$.

[6] Graff Zivin and Neidell (2013) set up a model to demonstrate how pollution affects health which is an indispensable component of human capital (Le et al., 2003; Wößmann, 2003; Benos and Zotou, 2014). In this study, we seek to establish a complementary work which exploits the reverse linkage through the lens of environmental awareness as emphasized in Graff Zivin and Neidell (2013).

Intuitively, the sign of $\frac{dE}{dA}$ is negative, and the term $\frac{dA}{dHC}$ is positive according to our previous discussion. At the macro level, the sign of $\frac{dA}{dH}$ remains positive.[7] The change, if any, is that the effect is reinforced through non-pecuniary externalities sustained by a larger stock of human capital (Sianesi and van Reenen, 2003). This is intuitive as more educated citizens would possess stronger bargaining power when demanding for environmental amenities. (Pargal and Wheeler, 1996; Sianesi and van Reenen, 2003; Ghanem and Zhang, 2014).

To sum up, combining the positive signed $\frac{dA}{dHC}$ with the negative signed $\frac{dE}{dA}$ reaches to the conclusion that $\frac{dE}{dHC}$ is negative, suggesting human capital helps to alleviate pollution.

While the conceptual model provides a clear prediction regarding the nexus between human capital and pollution, this model is silent on other variables which could potentially affect pollution. To address this issue, we rely on STIRPAT (**S**tochastic **I**mpacts by **R**egression on **P**opulation, **A**ffluence and **T**echnology) model (Dietz and Rosa, 1997). The model defines the reference pollution level (I_o) for a given level of production and consumption, and as an extension of the IPAT identity (Ehrlich and Holdren, 1971), it also decomposes aggregate environmental impact into population, affluence and technology effects. Compared to IPAT identity, the STIRPAT model offers a flexible approach for hypothesis testing and does not impose a priory proportionality in the functional relationships between factors (Liddle, 2013).

We choose the STIRPAT model over the competing Environmental Kuznets Curve (EKC) model to avoid two complications.[8] As discussed in Liddle (2013; 2015), the STIRPAT model avoids using the quadratic transformation of a nonstationary variable (e.g. real GDP per capita). Second, it relaxes the assumption that the population elasticity of environmental impact is a unity which makes the population variable redundant in the EKC framework.[9] Moreover, the STIRPAT model is developed to analyze aggregate environmental impacts rather than explaining emissions or pollution at per capita basis. Since policymakers care about aggregate emissions which matters greatly for the ecological sustainability, the STIRPAT model is more appropriate from this perspective.

In general, the STIRPAT model is written as follow:

$$I_{it} = aP_{it}^{b} A_{it}^{c} T_{it}^{d} e_{it} \tag{1}$$

[7] It important to note that the relationship between *A* and *HC* could be nonlinear. A special case is that human capital would not alter environmental awareness until a certain threshold in *HC* stock is achieved. As such, $\frac{dA}{dH}$ could be zero when the improvement in *HC* does not reach to the threshold value. We consider this issue in our empirical analysis.

[8] In an earlier version of this paper, EKC framework is also applied to examine the relationship between human capital and CO_2 emissions. While we found the qualitatively similar results for the nexus, EKC was not supported by provincial panel of China. This is also the primary reason which motivates us turning to STIRPAT model. Regression results using EKC model are available upon request.

[9] Note that in the EKC framework, population is not present as one of the right-hand variables. Instead, population is used to scaling environmental variable and other controls. It thus implicitly assumes that the coefficient attached to population is unity.

Where the subscript *i* denotes provinces of China and *t* refers to year. *a* is a constant and exponents *b*, *c* and *d* are elasticities of each variable. Specifically, *I* standards for reference level of environmental impact and *P*, *A* and *T* are populations, affluence and technology, respectively.

2.2 Empirical model

If we use CO_2 emissions as the proxy for the environmental impact, it is clear from the above discussion that the total emission is affected by the reference level of environmental impact given by *I* and the emission changes affected by human capital. Therefore, by transforming equation (1) into logarithm form and including human capital (HC_{it}), our empirical specification with provincial- and time-fixed effects becomes:

$$\ln(CO2_{it}) = \beta_1 + \beta_2 \ln P_{it} + \beta_3 \ln A_{it} + \beta_4 \ln T_{it} + \beta_5 \ln HC_{it} + \alpha_i + \gamma_t + \varepsilon_{it} \tag{2}$$

The theoretical predictions from the STIRPAT model suggest that β_2 and β_3 should be positive as a larger population and richer households would consume more natural resources on average. By contrast, β_4 is expected to be negative as the deployment of environmentally-friendly technologies would produce fewer pollutions during production. Following our conceptual discussion, we expect β_5, the coefficient of human capital, to be negative.[10] Regarding other controls, we employ real GDP per capita to proxy affluence (*A*). Following Liddle (2013) and Liddle (2015), technology (*T*) is captured by both energy intensity and economic structure. These two variables are also major forces in shaping CO_2 emissions.

It is important to note that the estimated coefficient of β_5 represents the reduced-form association between human capital and CO_2 emissions. There are other mitigating channels through which human capital would affect CO_2 emissions (Yao et al., 2019). For instance, human capital contributes to economic growth and technological innovations which in turn influence CO_2 emissions. We formally consider them in the section of sensitivity checks.

3. DATASET AND ESTIMATION STRATEGY

3.1 Dataset

For our empirical purpose, we construct a panel of 30 provinces over the period 1997–2016.[11] We focus on this period because the rapid growth of CO_2 emissions and reliable emission data are only available during this period.

[10] Note that when human capital is proxied by the number of average schooling years, the logarithm operation is not taken. If we take the logarithm of average schooling years, the estimated coefficient HC would be interpreted as β_5 percent reduction in CO_2 emissions due to one per cent improvement in average schooling years. Obviously, this interpretation is not intuitive. As such, we follow the literature estimating returns-to-education and does not take logarithm operation for the number of schooling years (Yao et al., 2018). In that way, the estimated coefficient of β_5 directly indicates us that how much per centage (β_5 ×100%) reductions in CO_2 emissions is due to a one-year improvement in average schooling years.

[11] We focus on this period because of data availability. Data used for constructing CO_2 emissions are not available until 1997 and the same data for the period 2017–2019 is not published yet.

Our key explanatory variable, human capital, is obtained from the China Center for Human Capital and Labor Market Research (CHLR hereafter). To measure it comprehensively, we have compiled a set of different proxies for the working-age population between 16 and 64 years old.[12] Our benchmark proxy is educational attainment in terms of average schooling years, on the basis that human capital embodied in workers is proportional to the number of formal schooling years (Wößmann, 2003). This proxy captures the overall development of human capital (Barro and Lee, 2013).

However, this aggregate measure mutes on the distribution of human capital across different age groups in which their human capital could exert heterogeneous impacts on CO_2 emissions. To test this hypothesis, we have also measured the average schooling years across three groups, specifically, for the cohorts of 16–24, 25–44, and 45–64 years old. The first splitting point is set to be 24 as it is the upper age bound for the majority of full-time Chinese students. The second splitting point is used to divide the young and older cohorts of full-time workers. We select splitting point 45 to balance two cohorts with each of them spanning 20 years. In order to show our results are not sensitive to these splitting points, we have performed robustness checks in Section 5 using an alternative grouping strategy.

The heterogeneity analysis across different age cohorts help us to understand the mechanisms through which human capital may affect pollution. If the human capital embodied in the 16–24 years old cohort is the main driving force to the negative human capital–CO_2 emissions association, the underlying mechanism is likely to operate through the non-production sector, as a considerable proportion of this cohort remains in school (Ge et al., 2018). While tertiary education is less common in developing countries like China, our dataset (1997–2016) is coincident with a nation-wide educational initiative that dramatically expanded the enrolments in tertiary education. According to the World Bank (2019), the gross college enrolment in China increased from 5.45 per cent in 1997 to 48.44 per cent in 2016. The rest half cannot access to tertiary education are mostly disadvantaged cohort from rural regions. Without proper qualifications, they usually end up with farming works or migrate to cities and sort into labour-intensive jobs (Yao et al., 2018).

Our second and third proxies of human capital are, respectively, the shares of the working-age population holding a high school degree and tertiary degree. Compared to school enrolment ratio that is commonly used in the literature, our measures are more integrated into production and therefore should exert a direct impact on emissions. Additionally, they emphasize on the quality aspect of the existing working force and can distinguish human capital into basic and advanced categories.[13] In other words, this setup allows us to examine human capital–CO_2 emissions nexus from the perspective of human capital quality.

Our CO_2 emission data are drawn from Shan et al. (2018a). To date, no annual, officially published CO_2 emission data exist at the provincial level of China. Scholars commonly estimate it following the *Guidelines for*

[12] This setup is according to Chinese Labor Law which stipulates that the youngest age allowed to work formally is 16 years old and the upper bound retirement age is 65 years old.
[13] One may suggest that basic human capital should also include the proportions of primary and junior high school degree holders (Li et al., 2014). However, due to the enforced Nine-Year Compulsory Education law, the variations in these educations are quite limited across provinces over our sample period. We have also examined their impacts on CO_2 emissions, but none of them are significant. Results are available upon request.

National Greenhouse Gas Inventories recommended by IPCC (Intergovernmental Panel on Climate Change). However, due to subjective coverage on different industries and fossil fuels, these estimates exhibit considerable discrepancies, with a gap could be large as total emissions of Russia (Shan et al., 2018a).

This uncertainty is addressed by Shan et al. (2018a) via the following improvements. The first is the consideration of 26 fossil fuels consumed in 47 industrial sectors, consistently for 30 provinces over the period 1997––2016.[14] The second is the adjustments made on carbon emission factors, which govern the chemical process from fuel combustion to CO_2 generation.[15] Existing estimates adopt the default values recommended by IPCC, which are approximately 40 per cent higher than the values obtained from surveying China's fossil fuel quality and industrial processes (Liu et al., 2015). Using updated, China-specific emission factors unambiguously improves estimation to a large extent, which considerably alleviates measurement errors. Third, Shan et al. (2018a) incorporated the process-related CO_2 emissions that are due to the cement production process. It is an important source of carbon emissions in China but has been largely ignored in previous estimations. Omitting it would severely bias the estimation downward given China is the top cement producer in the world. Finally, Shan et al. (2018a) employed both sectoral and reference approaches, which respectively employed energy consumption data and energy production data, to cross check their estimations.

Other variables suggested by STIRPAT framework, alongside additional controls and other pollution indicators used in sensitivity checks, are collected from a series of Chinese statistical publications, which are listed in Appendix A.

Table 1 defines and summaries all variables used in this study. The entire working-age population attains 9.15 years of formal schooling on average. Due to excluding retiree cohort, this figure is much higher than 7.45 years estimated by Barro and Lee (2013) over the similar period (Zhang et al., 2007). Meanwhile, there are large discrepancies across different age groups. Younger generations on average attain more formal schooling than their older counterparts. Moreover, we note that the share of high school degree holders almost doubles the share of tertiary degree holders, reflecting the nature of basic and advanced human capital. Regarding CO_2 emissions, reference approach produces higher estimations than the sectoral approach. For the estimation from the sectoral approach, much of CO_2 emissions are due to fossil fuel consumption, and particularly coal consumption.

[**Insert Table 1 about here**]

[14] For instance, Li et al. (2016) considered 8 fossil fuels whereas 9 was taken in Ren et al. (2014). However, none of them even recognized industrial heterogeneity in carbon emission factors like fossil fuel oxygenation efficiency, which refers to the oxidation ratio during fossil fuel combustion.

[15] The equation $CO2_{ij}=AD_{ij}\times NCV_i\times CC_i\times O_{ij}$ describes the relationship between fossil fuel consumption and CO_2 emissions. *i* refers to fossil fuel type and *j* refers to industrial sector. NCV_i is the net caloric value and CC_i is carbon content, both of which are fuel specifically. Meanwhile, O_{ij} is the oxygenation efficiency, which depends on fossil fuel and industry. These fossil fuel- and/or industrial- specific parameters are collectively known as emission factors. Shan et al. (2018a) offered a detailed explanation on them.

3.2 Econometric strategy

We estimate the long-run association between human capital and CO_2 emissions in Chinese provinces over the period 1997–2016. Since regional interdependencies are often presented due to economic, fiscal and political integrations, we need to account for such cross-sectional dependency to avoid related bias in our estimations (Pesaran, 2007; Westerlund, 2007). To examine whether our panel is subject to this issue, we perform the multiple cross-sectional dependence (CD) tests including Breusch and Pagan (1980) Lagrange multiplier (LM) test, the Pesaran (2004) scaled LM test, Baltagi et al. (2012) bias-corrected scaled LM test, and the Pesaran (2004) CD test.

We then apply panel unit root tests to find the order of integration in our variables. Since cross-sectional dependence might be presented in our panel, we perform the cross-sectionally augmented IPS panel unit root (CIPS) test (Pesaran, 2007) and compare it to the result from Im et al. (2003) (IPS) panel unit test. We implement both tests to demonstrate how a cross-sectionally dependent panel may affect the order of integration for our selected variables.

Having identified cross-sectional dependence and the order of integration in our panel, we perform a panel cointegration test. We carry out this test since our panel spans 20 years and the estimation of it is subject to spurious regression. If cointegration is found between the proxies of human capital and CO_2 emissions, the significant association between them cannot be considered as spurious (Greene, 2012). We conduct the Westerlund (2007) test, on the basis that it allows cross-sectionally dependence in the panel and imposes no common factor restrictions. While the Westerlund (2007) test displays desirable small-sample properties, the test results may be sensitive to the selections of lead and lag length in a short *T* panel like ours (Westerlund, 2007). Given that we have five variables over 20 years in the cointegrating space, we follow Salim et al. (2017) and seek to balance between the number of regressors and their lengths of lead and lag in the model. Specifically, we first apply the Westerlund (2007) test to a bivariate model with only human capital and carbon emissions in exchange for deep lead and lag lengths, before incorporating all other controls at the expense of reduced lead and lag lengths.

Our last step is to estimate the coefficient of human capital on CO_2 emissions. We begin with a fixed effects model that accommodates both time-invariant, provincial-specifically fixed effect and aggregate time effect that controls external shocks universal to all provinces. Meanwhile, fully modified OLS (FMOLS) estimator is employed to account for the cointegrating relationship between human capital and CO_2 emissions. To avoid biased estimates due to cross-sectional dependence, we also consider the augmented mean-group (AMG) estimator (Eberhardt and Teal, 2010). In general, AMG shares the spirit of Pesaran’s (2006) common correlated effects mean-group (CCEMG) that removes cross-sectional dependence in the panel by plugging the cross-sectional average of the dependent and independent variables as additional regressors in the model (Salim et al., 2017; Yao et al., 2019). Compared to CCEMG, AMG explicitly includes the time dummies to capture the unobservable common factors and performs better for a cross-sectionally dependent panel under the Monte Carlo simulation (Eberhardt and Teal, 2010).

4. EMPIRICAL RESULTS

Table 2 presents the results for the Breusch–Pagan LM, Pesaran scaled LM, bias-corrected scaled LM and Pesaran CD tests which share the null hypothesis that there is no cross-sectional dependence in our panel. The null hypothesis is consistently rejected, and we conclude that there is strong evidence of cross-sectional dependence among Chinese provinces. This finding is intuitive as a series of market reforms and standardization of the national education curriculum have increased provincial dependency in China over the post-reform period (Salim et al., 2017).

[**Insert Table 2 about here**]

Next, panel unit root tests are performed to ascertain the order of integration for selected variables. Table 3 reports the results for both IPS and CIPS tests. According to the IPS test, except *asy25t44, TerySch* and *EcoStc*, all variables are stationary after first differencing. CIPS test, by contrast, suggest all variables are integrated of order one. Since there is strong evidence of cross-sectional dependence in our panel, we prescribe to the CIPS test results and conclude that all variables are the first-differenced stationary.[16]

[**Insert Table 3 about here**]

Table 4 reports the results of Westerlund cointegration test, which assumes the null hypothesis of no cointegration among its four statistics (G_τ, G_α, P_τ and P_α).[17] For panel **A** where the bivariate model is focused, there is evidence of cointegration between CO_2 emissions and human capital captured by *asyT* and its counterparts across different age groups. Note that the evidence is much stronger for the cohort aged between 25 and 44. Meanwhile, the long-run association holds for the share of tertiary degree holders but not for the share of high school degree holders. Panel **B** adds affluence, population and technology effects suggested by the STIRPAT model, at the expense of reduced lag and lead length (Westerlund, 2007; Persyn and Westerlund, 2008). The long-run association in the multivariate model retains for human capital measured by *asy25t44* and *TerySch*.[18] These results appear to support a heterogeneous human capital–CO_2 emissions nexus across different age cohorts and by types of human capital. Specifically, both younger workers and workers with advanced human capital tend to exert a significant impact on CO_2 emissions.

[16] We also conduct the Carrion-i-Silvestre et al. (2005) cross-sectionally dependent panel unit root test with multiple structural breaks. Results are reported in Appendix B. In contrast to CPIS test, Carrion-i-Silvestre et al. (2005) test assume the null hypothesis of stationarity. We show that all of our variables are not stationary at level. Meanwhile, we have also tested their first differenced transformations and the results cannot reject the null hypothesis of stationarity (these results are available upon request). As such, the panel unit test which controls structural breaks has yielded the same conclusion from the CPIS test.

[17] G_τ and G_α refer to group-mean tests, which assume the coefficient of error-correction term is heterogeneous across cross-sectional units; while P_τ and P_α tests, known as panel tests, restrict the coefficient of error-correction term to be the same across all cross-sectional units.

[18] Since the Westerlund (2007) test assumes away structural breaks in the cointegrating relationship, we also apply the recently developed Banerjee and Carrion-i-Silvestre (2015) panel cointegration test with structural breaks in a cross-sectionally dependent panel. Results reported in Appendix are consistent with the Westerlund test results.

[**Insert Table 4 about here**]

Table 5 summaries the baseline results. It shows the impacts of human capital on CO_2 emissions across different age groups and by the quality of human capital. We begin with the impact of *asyT*, which captures the overall human capital for the entire working-age population. Column (1) finds that there is a negative and significant association between human capital and CO_2 emissions. Specifically, emissions will be reduced by 12 per cent for one additional year of formal schooling, all else equal.

However, this finding fails to hold across different age groups. As revealed from column (2) to (4), the negative association becomes much larger and more significant for the cohort of 25–44 years old, while a positive but insignificant relationship is found for the cohorts of 16–24 and 45–64 years old. These results indicate that the established negative association between human capital and CO_2 emissions is driven by the 25–44 years old cohort. Compared to the older generation, they attained 1.6 years more formal schooling (see Table 1) and were free from education chaos due to the 1966–1976 *Cultural Revolution*.[19] Given these quantity and quality advantages, the 25–44 years old cohort may possess better knowledge to acquire abatement practice and technology during the production process. While both advantages were also holding for the 16–24 years old cohort, a considerable proportion of them remains in school and yet to be full-time employed. As such, their contribution, if any, is expected to be quite limited.

On another dimension, our empirical human capital–CO_2 emissions nexus also differs from the quality of human capital. Columns (5) and (6) find that the negative and significant impact holds for advanced human capital but not for basic human capital. Specifically, a one per cent increase in the share of tertiary degree holders reduces CO_2 emissions by 5.7 per cent, all else equal. Why does advanced human capital matter for CO_2 reductions? We offer two explanations from household and production perspectives. First, households with advanced education are better informed about the risk of pollution exposure. It cautions them to carry out avoidance behaviors for themselves and, if any, to adopt a less harmful lifestyle to protect the environment for the future generations (Goetz et al., 1998; Graff Zivin and Neidell, 2013; ESRC, 2011). Second, workers with advanced human capital are crucial to the innovation and the diffusion of environmentally-friendly production technologies (Li and Lin, 2016; Lan and Munro, 2013).

To detect the possible nonlinear association between human capital and CO_2 emissions, we also estimate specifications incorporating the square term of *asy25t44* and *TerySch*. Results reported in columns (7) and (8) indicate that the estimated coefficients on the square term of both *asy25t44* and *TerySch* are small and insignificant. Meanwhile, including these squared terms does not change the magnitude and significance of *asy25t44* and *TerySch* much. These

[19] Formal education and the quality of it were severely hampered during 1966–1976 Cultural Revolution. See Meng and Gregory (2002) and Zhang et al (2007) for more detail information. Within the 25–44 years old group, people of the oldest cohort were born in 1972 and the legal year for them to enroll primary school is 1979, three years after the *Cultural Revolution*.

results suggest that the association between human capital and CO_2 emissions appears to be linear. As such, we will focus on the linear specification in the subsequent analysis.[20]

Since we have established that only selected human capital measures ("*asy25t44" and "TerySch"*) are cointegrated with CO_2 emissions, standard OLS estimator with two-way fixed effect may not able to produce long-run estimates efficiently. To address this concern, we apply FMOLS estimator, which employs a semi-parametric correction to eliminate the problems caused by the long run correlation between the cointegrating equation and stochastic regressors innovations (Phillips and Hansen, 1990). Results from columns (7) and (8) confirm our previous findings that the negative and significant human capital–CO_2 emissions nexus is driven by average schooling attained by 25–44 years old cohort and by advanced human capital. Moreover, columns (9) and (10) further control cross-sectional dependence using AMG estimator, and reassuringly, it leaves our findings qualitatively the same.

Our finding is in line with Goetz et al. (1998) which found a negative association between human capital pollution using the U.S. cross-state dataset. Notably, their finding is driven by the share of secondary degree holders while our negative association is due to tertiary degree holders. This inconsistency could be related to the differences in education systems between the two countries. According to Yao et al. (2018), high-school students in China mostly focus on exam-taking skills for qualifying college admission which carry little value in the real world.

As for the rest controls, results are largely consistent with theoretical predictions from the STIRPAT model. Affluence captured by real GDP per capita exerts a positive and highly significant impact on CO_2 emissions. Energy intensity, which is used to measure the general level of technology, is shown to be detrimental to the environment. The positive effect is also reported for the population. These findings are in line with Liddle (2013, 2015) who obtained similar results using cross-country panels.

As a final remark, we carry out CIPS and Pesaran CD tests on the estimated residuals from all specifications. Results show that they are stationary and free from cross-sectional dependence, suggesting our estimates are no longer biased by these issues.

[**Insert Table 5 about here**]

5. SENSITIVITY CHECKS

This section performs a set of sensitivity checks to further validate our findings. Table 6 reports them in alphabetical order.

[**Insert Table 6 about here**]

A: Potential outlier effects

[20] We also add squared terms of *asyT*, *asy16t24* and *HighSch* and estimate them using OLS, FMOLS, and AMG estimators. Results are consistent and suggest that nonlinearity between human capital and carbon emissions is not presented in our sample. To conserve space, these results are not reported, but available upon request.

We begin with dropping four municipalities, namely, Beijing, Tianjin, Shanghai and Chongqing. Due to their provincial-level administrative rankings, these megacities are attractive to young talents and are also subject to more stringent environmental regulations. The stylized facts concern us that our findings could be driven by these outliers. Columns (1) and (2) use the sample excluding them and confirm the negative and significant association between human capital and CO_2 emissions.

B: Alternative CO_2 estimation

Section **B** inquires whether our finding is sensitive to CO_2 estimation method. So far, our analysis has built on a sectoral approach, which relies on energy consumption data to estimate CO_2 emissions. By contrast, the reference approach, which is based on energy production and trade data, assumes that all the carbon elements from the primary energy sources are converted into CO_2 emissions. Since the reference approach does not exclude energy losses during transportation and any other non-energy purpose uses, it mechanically produces higher estimation and forms an upper bound of carbon emissions (see Table 1). Nevertheless, Columns (3) and (4) find that using reference CO_2 emission data does not change our findings qualitatively.

C: Alternative human capital proxy

Section **C** considers income-based human capital (*JFHC*) instead of education-based measures. While the education-based measures are readily available, an obvious shortcoming is that they fail to incorporate informal human capital in terms of working experience, on-the-site training and learning-by-doing (Le et al., 2003; Wößmann, 2003; Li et al., 2014). To examine whether they could alter our findings, we turn to income-based human capital, which is estimated by CHLR. It modified Jorgenson and Fraumeni's (1989, 1992) lifetime-income approach to estimate the monetary human capital stock which systematically incorporates the market value of all aspects of human capital services.[21] For the reason of consistency, we focus on the monetary human capital stock due to labor force cohort and scale it with the number of the working-age population.

According to columns (5) and (6), a one per cent increases in *JFHC* is shown to reduce sectoral CO_2 emissions by 0.67 per cent and reference CO_2 emissions by 0.18 per cent, respectively. Our finding is consistent with Lan and Munro (2013) and Salim et al. (2017), which concluded that energy-saving practices are assimilated and developed through working experience, on-the-site training, and learning-by-doing rather than taught explicitly at schools. As such, the government should also consider fostering informal human capital to alleviate global warming.

[21] In general, the Mincerian equation is used to separate the effects of educational and non-educational human capital on earnings. Li et al. (2014) provide a detailed description on how the Mincerian equation was applied to estimate individual earnings from various surveys and then how these estimated individual earnings are aggregated into monetary human capital stock.

D. Reverse causality

Section **D** addresses reverse causality from pollution to human capital. A handful of empirical studies have obtained the consistent evidence that pollution is detrimental to the human capital formation through worsening health status (Currie et al., 2009; Graff Zivin and Neidell, 2012; Graff Zivin and Neidell, 2013; Bharadwaj et al., 2017). To show that our findings are not due to this reverse linkage, we turn to the system GMM method which improves estimation efficiency given our variables are nonstationary at levels (Bound et al., 1995).

Columns (7) and (8) find that both *asy25t44* and *TerySch* retain their negative effects on carbon emissions despite the significance level is reduced to 5 per cent. Meanwhile, lagged CO_2 emissions has a coefficient of 0.73, indicating carbon emissions are highly path-dependent. Regarding diagnostic checks, both AR (1) and AR (2) statistics are negative but only the former is significant. Moreover, Hansen statistic is insignificant in both specifications, implying that the internal IV is appropriate. These tests consistently suggest that our models are correctly specified and properly identified.

We admit that identification via using external IV is preferred to using internal IV. However, as highlighted in Fleisher et al. (2010), macro variables are notoriously difficult to be instrumented as valid IV are often correlated with geographical factors and thus are fixed and perfectly collinear with provincial fixed effects. A more complicated fact is that we have several different and highly correlated proxies of human capital. To identify the causal effect of *asy16t24*, valid IV must be sufficiently correlated with it, but at the same time, it should not exert any effect on other human capital proxies like *asy25t44*. The same conditions are also applied to the IV for *asy25t44*. These demanding conditions made causal inference using external IV almost impossible.

Nevertheless, to further rule out the reverse causality from CO_2 emissions to human capital, we carry out Dumitrescu and Hurlin (2012) panel Granger test in Appendix D. This test allows cross-sectional heterogeneity and dependence. Reassuringly, we find that there is unidirectional Granger causality running from human capital to CO_2 emissions, consistently for two different proxies of human capital.

E: Distinguish the short- and long-run effects

Section **E** distinguishes human capital–CO_2 emissions association into short- and long-run via panel ARDL specification. This setup provides another way to test the cointegrating relationship between the two variables. There are three estimators designed for ARDL specification, and in our case, pooled mean grouped (PMG) estimator is selected over mean-grouped (MG) and dynamic fixed-effect (DFE) estimators according to join-Hausman test.[22]

[22] These estimators made different assumptions on the slope parameters of each cross-sectional unit. For example, DFE assumes constant short-run and long-run slope parameters, whereas MG allows the slope parameters to vary in both short and long run. Unlike DEF and MG, PMG permits the slope parameters to change in the short run but imposes homogeneous slope parameters across all cross-sectional units in the long run (Pesaran et al., 1999; Pesaran and Smith, 1995).

Column (9) and (10) confirm the negative association between human capital and CO_2 emissions in the long run and it is absent in the short run.[23] Meanwhile, error-correction terms are shown to be negative and highly significant for both human capital proxies. It implies that in the long run, the negative association is restoring equilibrium after receiving an external shock, providing further evidence that human capital is cointegrated with CO_2 emissions (Pesaran et al., 1999; Pesaran and Smith, 1995).

F: China-specific controls

Section **F** adds several China-specific controls to further alleviate omitted variable bias. Over the past two decades, China has seen unprecedented integration into the world economy and the profound institutional changes (Naughton, 2007; Meng, 2012; Meng et al., 2013). Their variations could be correlated with human capital accumulation, which leads us to find spurious results. To address this concern, we include the trade-to-GDP ratio to capture the degree of integration into the world economy. Meanwhile, to gauge the pace of institutional reforms, we employ urbanization ratio, the share of the non-state economy and the share of migrant workers into a province. These variables are defined in Table 1 and their sources are presented in Appendix A.

According to Columns (11) and (12), our finding sustains over including these China-specific controls. We also find that openness to trade has increased CO_2 over the past two decades. This is consistent with the pollution haven hypothesis that firms from advanced economies outsourced their energy-intensive industries to China where environmental standards are generally lower. Meanwhile, the private ownership ("*Non_state*") is shown to be positive and significant. While the efficiency gain from privatization would reduce energy waste and therefore carbon emissions, the scale effect due to a rapid expansion of domestically-owned private firms has offset the efficiency effect, resulting into a net increase of CO_2 emissions (Naughton, 2007). We also find that the share of migrant workers ("*Imgra*") exerts a positive and significant effect on carbon emissions. This is intuitive as migrant workers give up their farming works and find jobs in manufacturing industries which energy is a complementary input. Finally, we find that urbanization does not affect emissions in any significant manner.

G: Regional specific time effects

While the previous section has considered additional controls, our empirical model is still subject to omitted variables bias due to other important but unobserved variables. Examples of them include the degree of environmental stringency and energy price shocks at the provincial level. In the context of China, the central government establishes environmental regulations which are implemented by provincial-level governments with varying degree of enforcements (Ma and Ortolano, 2000; Wang, 2013). Meanwhile, energy prices in China are highly regulated for promoting industrialization (Naughton, 2007). These features have further complicated the pattern of CO_2 emissions.

[23] To conserve space, we did not report the short-run effect of human capital on CO_2 emissions which is insignificant for both measures of human capital. Results are available upon request.

In section **G**, we use region-by-time fixed effects to captures these important but unobserved variables. Including these fixed effects captures the process that how provinces with varying degree of absorptive capacities responses to the shocks initiated by the central government.[24]

Columns (13) and (14) reveal that the estimated coefficients of *asy25t44* and *TerySch* remain negative and significant and become slightly larger in magnitude after including the region-by-time fixed effects.

H: Spatial consideration

Section **H** extends spatial interaction to the human capital–CO_2 emissions nexus. An underlying assumption of our analysis is that the environmental impact of human capital is limited to its own administrative region and does not spill over to proximate provinces. We now relax it and use Spatial Durbin Model (SDM) that incorporates spatial-weighted human capital of bordering provinces.[25] To that end, we first construct a spatial-weighing matrix that captures the interactions among Chinese provinces over space. We prefer contiguity weighting matrix over distance-based one due to the following reason. Calculating the paired distance between two administrative units needs to define their centroids. While it is a simple task when the administrative units are small in geographical scale (e.g. community or village), these centroids become less representative in large administrative units like provinces in China (Huang et al., 2016). Existing literature has considered the centroids of provincial capital cities, but we suspect it is subject to aggregation bias as most economic activities are conducted outside of capital cities. The contiguity weighting matrix we employed is demonstrated as follows:

$$W = \begin{pmatrix} 0_{11} & 1_{12} & 0_{13} \\ 1_{21} & 0_{22} & 0_{23} \\ 0_{31} & 0_{32} & 0_{33} \end{pmatrix}$$

Element 1 refers to the case that two provinces share the common border with each other and 0 otherwise. Following this definition, only province 1 and 2 share the border. We have row-normalized W to facilitate interpretation following the suggestion of Elhorst (2014).

Columns (15) and (16) find that the own-effect of human capital remains negative and significant. However, spatial-weighted human capital is consistently insignificant for both human capital proxies. We do not report them to

[24] Our sample are grouped into six regions: North China (Beijing, Tianjin, Hebei, Shanxi and Inner Mongolia); Northeast China (Liaoning, Jilin and Heilongjiang); East China (Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi and Shandong); South Central China (Henan, Hubei, Hunan, Guangdong, Guangxi and Hainan); Southwest China (Chongqing, Sichuan, Guizhou and Yunnan); and Northwest China (Shaanxi, Gansu, Qinghai, Ningxia and Xinjiang), according to definition of China statistics.

[25] Following the suggestion of one referee, we have also carried out Moran's *I* statistic to test whether our dependent variables are spatially correlated. Appendix E presents the test results for both sectoral- and reference- based CO_2 emissions under three distance cut-offs (200km, 500km and 1000km). We find strong evidence that CO_2 emissions, regardless estimation approaches and distance cut-offs, are spatially correlated. This result justifies for the choice of Spatial Durbin Model (SDM).

conserve space. We also consider the alternative, distance-based, spatial-weighting matrix and find that it does not alter the results using contiguity weighting matrix. We omit them to conserve space.[26]

I: Combo treatment

Section **I** combines **A**, **D**, **F** and **G** to form the most saturated specification and reassuringly it leaves our major results qualitatively unchanged.

J: Finer age groups and educational qualifications

We have also divided the working-age population using much smaller age bins and replicated all analyses over again. Specifically, average schooling years is measured for cohorts with five years interval incrementally: 16–20, 21–25, 26–30, 31–35, 36–40, 41–45, 46–50, 51–55, 56–60 and 61–64 years old. We find that the negative and statistically significant association between human capital and CO_2 emissions is concentrated in the age cohorts of 26–30, 31–35 and 36–40, largely in line with our established result.[27]

We also differ tertiary degree holders into three-year college and four-year university degrees for a limited time span between 2002 and 2015. While both measures remain negative and highly significant, the effect is much stronger for the share of four-year university degree holders. It further reinforces our finding that advanced human capital is more important in abating carbon emissions.[28]

K. Indirect channel through R&D

Our analysis so far has focused on the direct association between human capital and CO_2 emissions. However, their association could be mitigated through the channel of research and development (R&D). R&D outcome, due to human capital accumulation, could improve production efficiency and reduce the waste of energy input (Awaworyi Churchill et al., 2019). As income grows, countries are better able to afford the investment in R&D and are, hence, better able to adopt efficient technologies (Romer, 1986; Romer 1990; Aghion and Howitt 1992; Dinda, 2004). More efficient technologies reduce the need to use dirty energy and promote clean energy consumption, therefore reducing carbon emissions (Yao et al., 2019). Li and Lin (2016) argued that human capital enables switching to energy-efficient technology during production, thus reducing greenhouse gas emissions in the process. Ang (2009) applied time series dataset from China and identified a negative relationship between technology transfer and CO_2 emissions. Using firm-level data, studies such as Cagno and Trianni (2013) and Cole et al. (2008) highlighted complementarities between human capital and R&D in promoting efficient energy use. The IEA (2008) estimated that technological progress,

[26] These unreported results are available upon request.
[27] Full regression results are available upon request.
[28] Full regression results are available upon request.

alongside investments in human capital and R&D, can lower global primary energy consumption by 18% to 26% which significantly reduces carbon emissions. To accommodate this indirect channel, we use a system of structural equations and estimate it with maximum likelihood estimator:

$$\ln(CO2_{it}) = \beta_1 + \beta_2 \ln P_{it} + \beta_3 \ln A_{it} + \beta_4 \ln T_{it} + \beta_5 \ln HC_{it} + \beta_6 \ln R\&D_{it} + \alpha_i + \gamma_t + \varepsilon_{it}$$

$$\ln R\&D_{it} = \gamma_1 + \gamma_2 \ln P_{it} + \gamma_3 \ln KS_{it} + \gamma_4 \ln FD_{it} + \gamma_5 \ln HC_{it} + \kappa_i + \eta_t + \mu_{it}$$

The first equation of this system is our baseline model (2) augmented with R&D outcome which is proxied by the number of granted patents. The second equation models R&D outcome as a function of income level (*A*), physical capital stock (*KS*), financial development (*FD*), and one proxy of our human capital. Their definition and source can be found in Table 1 and Appendix A, respectively.

Results are reported in columns (19) and (20) respectively for *asy25t44* and *TerySch*. Their estimated coefficients remain negative and highly significant. Note that the effect of *asy25t44* increases from 0.268 to 0.391 and similarly so for *TerySch* from 0.057 to 0.092. These changes are intuitive as the indirect effect, which work through technological advancement, has strengthened the effect of human capital on CO_2 emissions. Meanwhile, in line with the findings from Ang (2009) and Li and Lin (2016), there is a negative and significant association between R&D efforts and CO_2 emissions.[29] Our findings imply that the established human capital–CO_2 emissions nexus is not sensitive to incorporating the indirect channel through R&D.

6. FURTHER ANALYSIS

In this section, we use disaggregated emission data to examine the potential mechanisms through which human capital influences CO_2 emissions. The provincial aggregate emission data can be further separated by energy sources and end emitters. We first divide aggregate CO_2 emissions into two, mutually exclusive, components. One is the emissions from fossil energy consumption while the other one is called process-related emissions which are due to cement production.

Table 7 reports the results using these disaggregated CO_2 emissions. Columns (1) and (2) find that while both *asy25t44* and *TerySch* remain negative, the advanced human capital (*TerySch*) exerts a much larger effect in reducing process-related emissions. Note that this sort of emissions, by definition, has nothing to do with energy consumptions, the negative association should operate through technology effect which improves production efficiency. Indeed, over the past decade, many small, outdated cement mills have been closed and replaced with modern and capital-intensive production facilities. For instance, more efficient New Suspension and Preheater (NPS) kilns have gained popularity in the recent decade (Gao et al., 2017; Ke et al., 2013). To further show that the technology effect is at play, we have

[29] To conserve space, the estimated results for the R&D model is not reported but available upon request. In addition to R&D, we have also examined the indirect channel through economic growth and economic structure. A similar simultaneous equation system is constructed and estimated, and we obtained the qualitatively similar estimates as our baseline results. The full regression results are available upon request.

conducted a placebo test which considers basic human capital (captured by *HighSch*). As expected, *HighSch* cannot reduce process-related emissions because basic human capital exerts a limited effect on adopting advanced technology.

Considering the CO_2 emissions due to fossil fuel consumptions, columns (3) and (4) reveal similar results to our baseline findings in Table 5. However, the effects of human capital on CO_2 emissions are heterogeneous across different fossil fuels. Both proxies of human capital exert a larger impact on CO_2 emissions due to coal consumption. The estimated coefficients of *asy25t44* and *TerySch* increase to 0.354 and 0.077, respectively. However, when looking at emissions from non-coal fuels, columns (5) and (6) indicate that the human capital–CO_2 emissions nexus is positive although they are imprecisely estimated. We offer two explanations for this finding. First, non-coal fossil fuels are mainly natural gas and crude oil which account for a much smaller share in the energy mix of China. Second, the extent of energy substitution from coal to other but cleaner fuels is quite limited during our sample period. Although human capital accumulation may accelerate the substitution from dirty to cleaner energies, this effect is shown to be marginal at best (Shan et al. 2018b). Our findings collectively imply that the negative association between human capital and environment is mainly stemmed from abating coal related emissions.

The coal-related CO_2 emissions can be reduced by cutting coal consumption, which might be facilitated by human capital accumulation. While this mechanism is plausible, it overlooks the stylized fact that coal is a fundamental energy source to China and the extent to substitute it with alternative energies is quite limited (Shan et al. 2018b). To formally control this scale effect, we include total energy consumption or coal consumption in our baseline model and find that our negative human capital–CO_2 emissions association remains qualitatively the same.[30] This finding implies that the negative human capital–CO_2 emissions association is unlikely due to reducing coal consumption. A more compelling mechanism is through improving energy efficiency which reduces CO_2 emissions per unit of coal consumption.

[**Insert Table 7 about here**]

Next, we are also interested in the sectors where these mechanisms are at play. Preliminary evidence suggests that the negative association between human capital and CO_2 is dominated by production sector as the negative association is driven by human capital endowed in younger workers. Ideally, we should regress both industrial CO_2 emissions and household CO_2 emissions on human capital separately. The difference in estimated sign, magnitude and significance level of human capital would provide us with the answer to this question. Unfortunately, such dataset is not available, and we turn to alternative pollutant—sulfur dioxide (SO_2) which are systemically collected for industrial and household emitters. We admit that the potential damages and regulatory frameworks are different between CO_2 and SO_2 but still purse this approach as both pollutants are highly correlated during fossil fuel combustion process.

Table 8 shows that the negative and significant association is limited to industrial SO_2 emissions. For household SO_2 emissions, such relationship is absent. These results are line with the previous findings that the youngest cohort, who are mainly in schools, cannot alter negative human capital–CO_2 emissions nexus. We have also

[30] These results are available upon request.

experimented with other human capital proxies and find that the results remain insignificant for household SO_2 emissions. These results lend support to our claim that the production sector is the major place where the negative human capital–CO_2 emissions nexus materializes.

[**Insert Table 8 about here**]

7. CONCLUSION AND POLICY IMPLICATIONS

In this study, we examine the relationship between human capital and CO_2 emissions using the provincial panel of China over the period 1997–2016. We find a negative and significant relationship between them in the long run. This result is driven by human capital endowed in young workers aged between 25 and 44 and by workers with a tertiary degree. With disaggregated dataset by CO_2 sources and end emitters, we can identify the mechanisms through which human capital reduces CO_2 emissions. We obtain the implicit evidence that the negative association operates through technology effect and energy efficiency improvement. Moreover, all these mechanisms are shown to be limited to the production sector but absent in the household sector.

Our findings suggest that human capital could form a complementary, if not an alternative, tool to curb CO_2 emissions. Specifically, schools may consider teaching long-term damages associated with global warming to improve students' environmental awareness. On the production side, financial incentives should be offered to enterprises which provides energy/environment related training to their employees. For those firms in high energy/pollution intensity industries, they should recruit more professionals to innovate their production process toward environmentally-friendly way. Although this study finds that human capital fails to reduce pollution in the household sector, it points out an avenue for the policymakers to intervene. For instance, the public campaign should be promoted to strengthen households' environmental awareness which cautions them the potential damages associated with global warming. Meanwhile, the financial incentive should be offered to adopt renewable energies or energies with less environmental impacts. Recently, the Chinese government have launched a green home appliance plan targeting rural households. This strategy should be encouraged among urban households which consume the most of residential energy in China.

This study, to the best of our knowledge, is one of very few attempts to quantify the environmental benefits owning to human capital accumulation. Although we have suggested the potential mechanisms that might drive the negative association between human capital and CO_2 emissions, the concrete conclusion cannot be drawn without the support from micro-level evidence. We leave this for future research.

ACKNOWLEDGMENTS:

We thank the handling editor, Professor David Broadstock and five referees for their constructive comments. Yao Yao acknowledges the financial support from Shanghai Sailing Project by Shanghai Science and Technology Committee (Grant No. 20YF1434100).

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Table 1: Summary statistics

Variables	Definition	Unit	Obs.	Mean	Std. Dev.	Min	Max
CO2R	CO_2 emissions by ***reference*** approach, in log form	1 Tonne	600	18.849	0.942	14.914	21.164
CO2S	CO_2 emissions by ***sectoral*** approach, in log form	1 Tonne	600	18.812	0.876	15.790	20.552
CO2S_EC	CO_2 emissions due to total energy consumption, in log form	1 Tonne	600	18.754	0.872	15.761	20.496
CO2S_Coal	CO_2 emissions due to coal consumption, in log form	1 Tonne	600	18.274	0.908	14.648	20.050
CO2S_Clean	CO_2 emissions due to less polluted energy consumption, in log form	1 Tonne	600	15.226	2.139	0	17.707
CO2S_PR	CO_2 emissions due to production process (e.g. cement production), in log form	1 Tonne	600	15.857	1.122	12.206	17.853
SO2_indus	Industrial SO_2 emissions	1 Tonne	600	12.996	0.941	9.735	14.381
SO2_con	Residential SO_2 emissions	1 Tonne	390	11.033	1.197	6.163	13.531
asyT	Average schooling years for the entire working age population (16-64)	Years	600	9.148	1.082	6.326	12.214
asy16t24	Average schooling years for the population aged between 16 and 24	Years	600	10.256	1.137	6.801	12.945
asy25t44	Average schooling years for the population aged between 25 and 44	Years	600	9.423	1.095	6.789	12.983
asy45t64	Average schooling years for the population aged between 45 and 64	Years	600	7.759	1.294	4.414	11.174
HighSch	Share of working age population who holds senior high school degree	%	600	18.141	4.322	8.705	30.270
TerySch	Share of working age population who holds a tertiary degree	%	600	10.519	6.606	2.130	38.390
JFHC	J-F method based monetary human capital stock, constant 1985 price in log form	1RMB	600	11.293	0.547	10.069	12.895
Afflu	Affluence, captured by per capita real GDP in 1985 constant price level, in log form	1RMB	600	8.322	0.769	6.438	9.975
ppl	Total population, in log form	1 Capita	600	17.346	0.767	15.416	18.502
ECint	Energy intensity, Standard Coal Consumed to produce 10,000 RMB GDP (1985 constant price), in log form	STC/10,000	600	-16.798	0.477	-17.815	-15.531
EcoStc	Economic structure, captured by industrial value added to total GDP	%	600	45.359	7.828	19.735	59.045
Urb_ratio	Urbanization ratio, the share of people living in the urban areas	%	600	47.352	15.78	21.53	89.6
Trade_shr	Share of trade to GDP	%	600	2.647	2.471	0.067	16.448
Non_state	Share of non-state sector economy, measured by the share of workers in non-state sectors	%	600	54.355	19.254	11.3	90.882
Imgra	Share of, inter-provincial, temporal migration workers, defined as the total population minus local *hukou* registered population, scaled by the total population	%	600	3.200	13.602	-19.699	68.616
R&D	Number of invention patents granted in log form	-	600	8.918	1.821	2.303	13.131
KS	Estimated per capita physical capital stock at 1985 constant price level in log form	1RMB	600	9.536	0.958	7.469	12.304
FD	The estimated proportion of total credit granted to private investors in log form	%	600	-0.751	0.247	-1.796	-0.146

Note: Data is compiled for 30 provinces over the 1997–2016 period. Appendix A provides the data sources for each variable.

Table 2 Cross-sectional dependence, by variables and testing procedures

	Breusch-Pagan LM	Pesaran scaled LM	Bias-corrected scaled LM	Pesaran CD
CO2R	7212.462 [0.000]	229.778 [0.000]	228.944 [0.000]	84.806 [0.000]
CO2S	7557.573 [0.000]	241.478 [0.000]	240.645 [0.000]	86.848 [0.000]
CO2S_EC	7512.681 [0.000]	239.956 [0.000]	239.123 [0.000]	86.594 [0.000]
CO2S_Coal	6402.631 [0.000]	202.322 [0.000]	201.488 [0.000]	77.258 [0.000]
CO2S_Clean	5638.010 [0.000]	176.399 [0.000]	175.565 [0.000]	68.933 [0.000]
CO2S_PR	6725.312 [0.000]	213.262 [0.000]	212.428 [0.000]	79.253 [0.000]
SO2_indus	2848.335 [0.000]	81.8197 [0.000]	80.9864 [0.000]	37.383 [0.000]
SO2_con	1963.005 [0.000]	51.8042 [0.000]	50.5542 [0.000]	18.760 [0.000]
asyT	8113.592 [0.000]	260.329 [0.000]	259.495 [0.000]	90.071 [0.000]
asy16t24	7530.431 [0.000]	240.558 [0.000]	239.724 [0.000]	86.293 [0.000]
asy25t44	8083.792 [0.000]	259.318 [0.000]	258.485 [0.000]	89.905 [0.000]
asy45t64	7949.639 [0.000]	254.770 [0.000]	253.937 [0.000]	89.136 [0.000]
HighSch	5317.125 [0.000]	165.512 [0.000]	164.686 [0.000]	36.387 [0.000]
TerySch	8048.148 [0.000]	258.110 [0.000]	257.277 [0.000]	89.698 [0.000]
JFHC	8165.667 [0.000]	262.094 [0.000]	261.261 [0.000]	90.362 [0.000]
Afflu	8167.045 [0.000]	262.141 [0.000]	261.308 [0.000]	90.370 [0.000]
ppl	4871.891 [0.000]	150.425 [0.000]	149.591 [0.000]	42.184 [0.000]
ECint	6187.832 [0.000]	195.039 [0.000]	194.206 [0.000]	77.219 [0.000]
EcoStc	3635.656 [0.000]	108.512 [0.000]	107.679 [0.000]	34.733 [0.000]

Note: p-values are provided in the brackets. The null hypothesis of all tests assumes no cross-sectional dependence.

Table 3 Panel unit root test, by variables and testing procedures

	IPS		CIPS	
	Level	First difference	Level	First difference
CO2R	3.706	-5.473***	-1.188	-4.331***
CO2S	2.466	-4.524***	-1.337	-4.145***
CO2S_EC	2.517	-4.935***	-1.121	-3.882***
CO2S_Coal	2.816	-4.589***	-1.322	-4.737***
CO2S_Clean	2.362	-10.170***	-0.885	-3.104***
CO2S_PR	2.446	-3.304***	-1.050	-3.774***
SO2_indus	1.527	-5.660***	-1.373	-4.273***
SO2_con	0.168	-3.123***	-0.684	-4.273***
asyT	5.105	-2.674***	-0.031	-1.760**
asy16t24	2.701	-2.790***	-0.820	-1.694**
asy25t44	10.727	-1.203	-0.185	-1.616**
asy45t64	-0.326	-3.663***	-0.554	-2.225***
HighSch	5.276	-4.563***	-0.178	-1.617**
TerySch	11.111	-1.038	0.507	-1.975***
JFHC	3.510	3.510***	0.056	-2.146***
Afflu	3.510	0.569	0.075	-2.730***
ppl	0.556	-6.109***	-0.549	-2.721***
ECint	6.454	-7.929***	-1.459	-4.082***
EcoStc	1.537	0.134	-0.606	-2.796***

Note: ***, ** and * denote the significance level at 1%, 5% and 10 %, respectively. The null hypothesis of both tests is that the variable is nonstationary. For the CIPS test, the maximum lag is set to 2 and the BG lag is set to 9. For the IPS test, the lag length is selected by minimizing the Akaike Information Criterion (AIC).

Table 4: Westerlund (2007) panel cointegration test with cross-sectional dependence, by HC proxies and testing procedures

Panel A: bivariate model	*asyT*	*asy16t24*	*asy25t44*	*asy45t64*	*HighSch*	*TerySch*
G_τ	-1.862 [0.140]	-1.608 [0.240]	-2.722 [0.000]	-1.963 [0.080]	-0.774 [0.960]	-3.473 [0.000]
G_α	-2.002 [0.570]	-1.735 [0.930]	-1.437 [0.905]	-2.344 [0.190]	-1.213 [0.960]	-1.447 [0.930]
P_τ	-11.54 [0.030]	-9.290 [0.000]	-10.37 [0.000]	-3.456 [0.400]	-4.704 [0.380]	-7.660 [0.000]
P_α	-3.068 [0.040]	-2.562 [0.080]	-2.744 [0.000]	-2.603 [0.000]	-0.903 [0.710]	-3.295 [0.040]
Panel B: Multivariate model	*asyT*	*asy16t24*	*asy25t44*	*asy45t64*	*HighSch*	*TerySch*
G_τ	-2.952 [0.060]	-2.999 [0.070]	-3.241 [0.055]	-2.801 [0.080]	-2.657 [0.090]	-4.055 [0.020]
G_α	-3.623 [0.740]	-4.455 [0.280]	-3.730 [0.665]	-3.700 [0.550]	-4.822 [0.110]	-3.902 [0.520]
P_τ	-13.21 [0.000]	-10.44 [0.410]	-16.10 [0.040]	-10.11 [0.300]	-10.75 [0.440]	-21.22 [0.020]
P_α	-2.608 [0.740]	-3.243 [0.520]	-7.754 [0.000]	-2.368 [0.850]	-4.928 [0.160]	-8.219 [0.000]

Note: robust p-values are provided in the brackets. The null hypothesis of all tests is that there is no cointegrating relationship among variables investigated. All tests incorporate an intercept but no trend. For the univariate model, the lead and lag length are set to 2, respectively. For the multivariate model, the lead and lag lengths are set to 0 and 1, respectively. For both models, the Bartlett kernel window width is set according to $4(T/100)^{2/9} \approx 3$. Bootstrap error is based on 100 repetitions.

Table 5: Baseline results

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS	(7) OLS	(8) OLS	(9) FMOLS	(10) FMOLS	(11) AMG	(12) AMG
asyT	-0.118**											
	(0.058)											
asy16t24		0.061										
		(0.040)										
asy25t44			-0.268***				0.240***		-0.203***		-0.212***	
			(0.056)				(0.049)		(0.000)		(0.101)	
(asy25t44)^2							-0.0003					
							(0.0003)					
asy45t64				0.062								
				(0.460)								
HighSch					-0.006							
					(0.008)							
TerySch						-0.057***		-0.052***		-0.047***		-0.060***
						(0.011)		(0.013)		(0.003)		(0.015)
(TerySch)^2								-0.0001				
								(0.0002)				
Afflu	1.215***	1.119***	1.252***	1.107***	1.167***	1.374***	1.274***	1.362***	0.783***	1.274***	0.737***	0.711***
	(0.102)	(0.102)	(0.103)	(0.104)	(0.108)	(0.099)	(0.103)	(0.103)	(0.001)	(0.008)	(0.125)	(0.114)
ppl	0.469***	0.602***	0.487***	0.549***	0.433**	1.299***	(0.961)	1.361***	1.048***	0.774***	0.617	0.870
	(0.171)	(0.195)	(0.185)	(0.163)	(0.177)	(0.235)	(0.231)	(0.253)	(0.000)	(0.005)	(0.471)	(0.579)
ECint	1.041***	1.025***	0.978***	1.004***	1.046***	0.889***	0.874***	0.871***	0.430***	0.960***	0.398***	0.247***
	(0.078)	(0.079)	(0.072)	(0.084)	(0.083)	(0.074)	(0.076)	(0.086)	(0.000)	(0.009)	(0.142)	(0.101)
EcoStc	-0.001	-0.001	-0.003	-0.001	-0.001	-0.005**	-0.005**	-0.005**	0.022***	0.047***	0.007**	0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.000)	(0.006)	(0.003)	(0.005)
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Provincial fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	Yes	Yes
R^2	0.963	0.963	0.964	0.963	0.962	0.965	0.965	0.965	0.998	0.898	0.967	0.912
CIPS on residual	-1.977***	-2.137***	-1.745**	-1.935***	-2.307***	-1.958***	-2.030***	-2.056***	-1.881**	-1.977***	-2.401***	-2.348***
Pesaran CD on residual	1.353	2.475**	1.169	1.138	2.938***	1.338	1.123	1.312	1.021	0.987	0.887	0.821
No. of Obs.	600	600	600	600	600	600	600	600	600	600	600	600

Note: Robust standard errors are reported in parentheses. ***, ** and * denote the significance level at 1%, 5% and 10 %, respectively. The null hypothesis of CIPS tests is that the variable is nonstationary. The null hypothesis of Pesaran CD test assumes no cross-sectional dependence.

Table 6: Sensitivity checks

	A		***B***		***C***		***D***		***E***		***F***	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Lagged CO_2							0.736***	0.728***				
							(0.088)	(0.098)				
asy25t44	-0.273***		-0.057**				-0.227**		-0.334***		-0.204***	
	(0.061)		(0.024)				(0.102)		(0.031)		(0.061)	
TerySch		-0.063***		-0.021***				-0.031**		-0.037***		-0.028***
		(0.014)		(0.005)				(0.015)		(0.008)		(0.013)
JFHC					-0.669***	-0.177***						
					(0.160)	(0.077)						
Error Correction									-0.383***	-0.436***		
									(0.067)	(0.058)		
Urb_ratio											-0.007	-0.009**
											(0.004)	(0.004)
Trade_shr											0.034***	0.029***
											(0.001)	(0.001)
Non_state											0.005**	0.005***
											(0.004)	(0.002)
Imgra											-0.026***	-0.024***
											(0.004)	(0.004)
Basic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Provincial fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region×Year fixed effect	No	No	No	No	No	No	No	No	No	No	No	No
AR(1)							-2.83***	-2.70***				
AR(2)							-0.38	-1.27				
Hansen statistic							8.11	4.73				
R^2	0.966	0.966	0.991	0.992	0.964	0.991					0.968	0.967
No. of obs.	520	520	600	600	600	600	570	570	570	570	600	600

Note: robust standard errors are reported in parentheses. ***, ** and * denote the significance level at 1%, 5% and 10 %, respectively. Robustness check ***A***= drop four municipalities (Beijing, Tianjin, Shanghai and Chongqing); ***B***=use CO_2 emissions by reference approach; ***C***=use estimated monetary based human capital stock derived from J-F lifetime method; ***D***=consider endogeneity of human capital using system GMM estimator; ***E***=distinguish between short- and long-run effect of human capital using PMG estimator; ***F***=add China-specific controls. ***G***=controls regional time-specific fixed effects. ***H***=consider spatial interactions. I is a combo of A, D, F and G. ***K*** considers indirect channel through R&D

Table 6: Sensitivity checks (continues)

	G		*H*		*I=A+D+F+G*	*J*	*K*	
	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
Lagged CO_2					0.744***	0.684***		
					(0.100)	(0.118)		
asy25t44	-0.332***		-0.197***		-0.181**		-0.391***	
	(0.063)		(0.007)		(0.091)		(0.059)	
TerySch		-0.032***		-0.014***		-0.007**		-0.092***
		(0.011)		(0.004)		(0.003)		(0.015)
JFHC								
R&D							-0.231***	-0.227***
							(0.012)	(0.011)
Urb_ratio					-0.004	-0.012		
					(0.009)	(0.009)		
Trade_shr					0.034***	0.029***		
					(0.001)	(0.001)		
Non_state					-0.005	-0.003		
					(0.005)	(0.004)		
Imgra					-0.007	-0.006		
					(0.005)	(0.005)		
Basic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Provincial fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region×Year fixed effect	Yes	Yes	No	No	Yes	Yes	No	No
AR(1)					-3.11***	-2.84***		
AR(2)					-1.47	-1.56		
Hansen statistic								
R^2	0.973	0.972	0.964	0.936	0.921	0.891	NA	NA
No. of obs.	600	600	600	600	520	520	600	600

Note: as above.

Table 7: Mechanisms by disaggregating CO_2 sources

	Production process		All fossil fuels		Coal		Non-coal	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
asy25t44	-0.093*		-0.263***		-0.354***		0.0001	
	(0.055)		(0.026)		(0.044)		(0.256)	
TerySch		-0.056***		-0.059***		-0.077***		0.071
		(0.013)		(0.006)		(0.009)		(0.076)
Basic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Energy consumption	NA	NA	Yes	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Provincial fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.976	0.977	0.990	0.991	0.979	0.980	0.557	0.558
No. of obs.	600	600	600	600	600	600	600	600

Note: Robust standard errors are reported in parentheses. ***, ** and * denote the significance level at 1%, 5% and 10 %, respectively.

Table 8: Extensions by using alternative air pollution

	Industrial SO_2 emissions		Household SO_2 emissions	
	(1)	(2)	(3)	(3)
asy25t44	-0.233***		-0.182	
	(0.066)		(0.122)	
TerySch		-0.053***		-0.011
		(0.016)		(0.022)
Basic controls	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes
Provincial fixed effect	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes
R^2	0.972	0.973	0.939	0.938
No. of obs.	390	390	390	390

Note: Robust standard errors are reported in parentheses. ***, ** and * denote the significance level at 1%, 5% and 10 %, respectively.

APPENDICES:

Appendix A: Data sources

Variables	Source(s)
CO2R	Shan, Guan & Zheng et al. (2018a)
CO2S	Shan, Guan & Zheng et al. (2018a)
CO2S_EC	Shan, Guan & Zheng et al. (2018a)
CO2S_Coal	Shan, Guan & Zheng et al. (2018a)
CO2S_Clean	Shan, Guan & Zheng et al. (2018a)
CO2S_PR	Shan, Guan & Zheng et al. (2018a)
SO2_indus	China Statistical Yearbook of Environment (2004-2017); China Statistical Yearbook (2004-2017)
SO2_con	China Statistical Yearbook of Environment (2004-2017); China Statistical Yearbook (2004-2017)
asyT	China Center for Human Capital and Labor Market Research (CHLR)
asy16t24	China Center for Human Capital and Labor Market Research (CHLR)
asy25t44	China Center for Human Capital and Labor Market Research (CHLR)
asy45t64	China Center for Human Capital and Labor Market Research (CHLR)
HighSch	China Center for Human Capital and Labor Market Research (CHLR)
TerySch	China Center for Human Capital and Labor Market Research (CHLR)
JFHC	China Center for Human Capital and Labor Market Research (CHLR)
Afflu	China Statistical Yearbook (1998-2017)
ppl	China Statistical Yearbook (1998-2017)
ECint	China Energy Statistical Yearbook (1998-2017); China Statistical Yearbook (1998-2017)
EcoStc	Online of National Data maintained by NBS: http://data.stats.gov.cn/english/easyquery.htm?cn=E0103
Urb_ratio	China Population & Employment Statistics Yearbook (1998-2017)
Trade_shr	China Statistical Yearbook (1998-2017)
Non_state	China Labour Statistical Yearbook (1998-2017)
Imgra	China Population & Employment Statistics Yearbook (1998-2017)
R&D	China Statistical Yearbook (1998-2017)
KS	China Statistical Yearbook (1998-2017)
FD	Almanac of China's Finance and Banking (1998-2017)

Appendix B Carrion-i-Silvestre et al. (2005) panel unit root test with

Variables	Carrión-i-Silvestre et al. (LM(λ))		Break Location (T_b)
	Test	**Bootstrap Critical Value (5%)**	
CO2R			
$\Psi_{\bar{t}}$	-5.5464058**	-4.8245164	1998, 2000, 2004, 2012, 2014
$\Psi_{\overline{LM}}$	-55.722259 **	-46.652524	
CO2S			
$\Psi_{\bar{t}}$	-5.1791922**	-4.8496594	2001, 2006, 2012, 2014
$\Psi_{\overline{LM}}$	-49.249202**	-46.964128	
CO2S_Coal			
$\Psi_{\bar{t}}$	-4.9402440**	-4.8611421	2003, 2013, 2014
$\Psi_{\overline{LM}}$	-46.964610**	-45.251437	
CO2S_Clean			
$\Psi_{\bar{t}}$	-6.3456868**	-4.8903187	2001, 2005, 2012, 2014
$\Psi_{\overline{LM}}$	-75.684061**	-48.013073	
CO2S_PR			
$\Psi_{\bar{t}}$	-5.9226775**	-4.7351567	1997, 1998, 2012 , 2014
$\Psi_{\overline{LM}}$	-62.458886**	-44.940383	
SO2_indus			
$\Psi_{\bar{t}}$	-4.9744983**	-4.8029729	2005, 2006, 2014
$\Psi_{\overline{LM}}$	-46.696109**	-45.459133	
SO2_con			
$\Psi_{\bar{t}}$	-6.4891595**	-4.8463185	2003, 2005, 2007, 2008, 2014
$\Psi_{\overline{LM}}$	-78.463430**	-47.339633	
asyT			
$\Psi_{\bar{t}}$	-5.7638507**	-4.7502097	1997, 2014
$\Psi_{\overline{LM}}$	-59.307397**	-45.185596	
asy16t24			
$\Psi_{\bar{t}}$	-5.7410819**	-4.7542567	2001, 2014
$\Psi_{\overline{LM}}$	-62.308140**	-45.243670	
asy25t39			
$\Psi_{\bar{t}}$	-5.5430390**	-4.7502097	2014
$\Psi_{\overline{LM}}$	-58.297809**	-45.185596	
asy40t64			
$\Psi_{\bar{t}}$	-6.4620849**	-4.8292389	2012, 2014
$\Psi_{\overline{LM}}$	-77.819211	-46.813964	
HighSch			
$\Psi_{\bar{t}}$	-6.0474471**	-4.8131857	1997, 2004, 2014
$\Psi_{\overline{LM}}$	-68.737468**	-46.286239	
TerySch			
$\Psi_{\bar{t}}$	-5.6050301**	-4.8434744	2000, 2014
$\Psi_{\overline{LM}}$	-59.546113**	-46.979295	

Variables	Carrión-*i*-Silvestre et al. (LM(λ))		Break Location (T_b)
	Test	**Bootstrap Critical Value (5%)**	
JFHC			
$\Psi_{\bar{t}}$	-6.8241824**	-4.8469607	2014
$\Psi_{\overline{LM}}$	-86.093274**	-47.118913	
Afflu			
$\Psi_{\bar{t}}$	-6.3406314**	-4.6532758	2014
$\Psi_{\overline{LM}}$	-75.100675**	-43.470365	
Ppl			
$\Psi_{\bar{t}}$	-5.0419748**	-4.7460604	2010, 2013
$\Psi_{\overline{LM}}$	-46.789928**	-45.050530	
ECint			
$\Psi_{\bar{t}}$	-6.5827311**	-4.7334462	2014
$\Psi_{\overline{LM}}$	-80.532354**	-44.828221	
EcoStc			
$\Psi_{\bar{t}}$	-5.0966172**	-4.8380289	2000, 2011, 2012, 2014
$\Psi_{\overline{LM}}$	-49.872350**	-47.177341	

Note: The number of unknown structural break is set to be 5. The null of LM (λ) test implies stationarity. We have used msbur.src code developed by Ng & Perron (2001). We ran similar estimations as offered in Table 3 of Carrion-i-Silvestre, J. L., Del Barrio-Castro, T., & López-Bazo, E. (2005). Here the long-run variance is estimated using Bartlett spectral kernel with automatic spectral window bandwidth selection as in Andrews (1991), Andrews and Monahan (1992) and Sul et al. (2003). The bootstrap distribution is based on 2,000 replications. The maximum lag order has been selected by $4(T/100)^{2/9}$ where T is the number of time series observations. ***, ** and * indicate that the test statistics is significant at 1%, 5%, and 10% levels, respectively.

Appendix C: Banerjee and Carrion-i-Silvestre (2015) panel cointegration test with structural breaks

Dependent Variable	z^*	**Panel data test statistic [** $t^{\tau}_{\tilde{e}_i^*}(\lambda_i)$ **]**	$\hat{r}$	$\hat{r}^P$	$\hat{r}_1^{NP}$
The model I: with ***asyT*** representing human capital	-7.59	-6.31	9	4	6
Model II: with ***asy25t39*** representing human capital	-10.33	-5.72	12	5	5
Model III: with ***TerySch*** representing human capital	-12.43	-5.38	7	6	4

Note: Maximum numbers of factors allowed is r_{max}=12. BIC in Bai and Ng (2004) is employed to estimate the optimum number of common factors ($\hat{r}$). Specifically, we implemented gauss procedures brkcoint.gss, brkfactors_heterog_2sb.gss to develop estimations for Banerjee and Carrion-i-Silvestre (2015) panel cointegration test with structural breaks. Our results are similar to Table V of Banerjee and Carrion-i-Silvestre (2015). An elaborated description of the procedures implemented could be found in page 20 of Banerjee and Carrion-i-Silvestre (2015).

Appendix D: Dumitrescu and Hurlin (2012) panel Granger test

Null hypothesis	**HC** does not Granger cause $\mathbf{CO_2}$			$\mathbf{CO_2}$ does not Granger cause **HC**		
Test statistics	$\bar{W}$	$\bar{Z}$	$\tilde{Z}$	$\bar{W}$	$\bar{Z}$	$\tilde{Z}$
asy25t39	11.159	18.244***	8.980***	3.583	1.303	-0.338
TerySch	13.752	24.042***	12.168***	5.610	2.837**	1.156

Note: lags length is set to be 3. To control cross-sectional dependence, all tests are performed based on the bootstrap method with 500 replications.

Appendix E: Moran's *I* test for global spatial autocorrelation

Distance cut-offs (km)	$\mathbf{CO_2}$ **emissions sector approach**	$\mathbf{CO_2}$ **emissions reference approach**
200km	0.626***	0.596***
500km	0.283***	0.251***
1000km	0.102***	0.103***

Note: The Moran's *I* lies within the range [-1, 1]. When a positive (negative) value of Moran's *I* is observed, this indicates that positive (negative) spatial autocorrelation for the variable exists across space. We use STATA code "moransi" to perform the test.