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ENERGY TOWARDS TARGETS? – THE ROLE OF
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Do Countries Adjust the Carbon Intensity of Energy Towards Targets? – The Role of Financial Development on the Adjustment

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Abstract

A sign of emerging downward trends in the carbon intensity of energy (CO₂ intensity) is an early indicator of progress in transitioning to low-emission energy. To trade off the obligation of reducing carbon emissions against the cost saving benefits of using fossil fuels, a country may choose an optimal share of use of low-emission energy. We use the partial adjustment model based on the trade-off theory of firms' capital structure to investigate whether countries adjust their CO₂ intensities towards specific targets. Using the sample covering 62 economies from 1992 to 2013, we find that the gaps between their actual and target CO₂ intensities narrow over time, suggesting adjustment towards their optimal levels of the use of low-emission energy. Countries with a higher degree of financial development display faster downward than upward speeds of adjustment towards targets. However, the opposite applies to countries with a lower degree of financial development. Consistently, countries with a higher (lower) degree of financial development adjusted their CO₂ intensities faster (slower) downward and slower (faster) upward towards their targets. Such findings are not related to the state of economic development of the countries. This demonstrates that financial development plays an important role in mitigating CO₂ emissions.

Keywords: CO₂ emissions, carbon intensity of energy, financial development, trade-off theory

JEL classification: Q5

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1. Introduction

To hold the increase in the global average temperature to well below 2°C above pre-industrial levels, as stated in the Paris Agreement, requires a consistent and harmonised approach to track progress at different levels of detail and indicators over different time periods. Given that CO₂ emissions are particularly relevant due to their dominant role in climate policy and their long-lasting effect on the climate system, tracking progress nationally to assess historical and future trends in CO₂ emissions is relevant to policy implementation for alleviating climate change [see Nakicenovic (1997), Raupach et al. (2007), Blanco et al. (2014), Steckel et al. (2015)]. The Kaya Identity is one such approach, in which different components form an interconnected and nested structure as illustrated in Figure 1. The commonly used Kaya-derived components (indicators) for monitoring the current trends include: total CO₂ emissions in level 1; energy intensity of GDP (energy/GDP) and CO₂ per energy unit in level 2; and CO₂ intensity of fossil fuels and share of fossil fuels in total energy use in level 3. These components are important energy related indicators for emission scenario analysis used by Nationally Determined Contributions (NDCs).

In this paper, we study the dynamics of the carbon dioxide intensity of energy (CO₂/energy henceforth CO₂ intensity), which is also known as the “carbonisation index” in the energy and environmental literature. According to the metadata description from the World Bank, CO₂ intensity is “*the ratio of carbon dioxide per unit of energy, or the amount of carbon dioxide emitted as a result of using one unit of energy in production.*” As noted in Herzog et al. (2006), Peters et al. (2017) and Lima et al. (2017), CO₂ intensity is measured broadly by two key components, namely CO₂ intensity of fossil energy and fossil share in energy. While the energy intensity (energy/GDP) has trended downwards historically and in the long term, Peters et al. (2017) show that based on emission scenarios consistent with the Paris Agreement, stringent climate policy is only expected to slightly accelerate historical improvements in energy intensity compared to baseline scenarios. In contrast, the scenarios indicate that significant mitigation is achieved by deep and sustained reductions in the CO₂ intensity,

indicating that most of the future mitigation will be due to sustained reductions in CO₂ intensity and CO₂ emissions, which should grow at a slower rate than GDP. The declines in CO₂ intensity are an important long-run signal showing that as economies develop, they are less reliant on high-emission fuels, become more efficient, and shift to services.¹ In addition, there is a trend emerging of a decline in CO₂ intensities of energy in large economies including China and the US. This sign of an emerging downward trend in CO₂ intensity is an early indicator of progress in climate change mitigation. And, economies with such trends may not necessarily have slower GDP growth. Compared to other commonly used indicators (such as CO₂ per unit of GDP, CO₂ per capita and total CO₂ emissions), CO₂ intensity, which is less affected by the boom and bust of economic activities and population changes, measures the efficiency of energy production in terms of CO₂ emissions more precisely.² Therefore, it is important to study the dynamics of CO₂ intensity in relation to climate change mitigation, and how countries adjust their CO₂ intensity dynamics.

The Kyoto Protocol began the process of securing countries' commitments to reduce greenhouse gas emissions as they have to lower their CO₂ intensities to achieve this objective. However, the process of lowering the intensities by substituting fossil fuels with renewables or coal with natural gas is costly, in particular for those countries with substantial economic growth. Feng et al. (2015) and Le Quere et al. (2019) point out that slower GDP growth among developed countries in part contributed to the slowing of their total CO₂ emissions over the past decade, whereas fast developing countries, such as China, India and Indonesia, have significantly larger shares of CO₂ emissions. To promote faster economic growth, it is natural for countries to increase the level of consumption and also accelerate their electricity production, thus possibly increasing the use of fossil fuel energy.³ This

¹ See Blanco et al. 2014.

² Filipović, et al. (2015) show that among EU-28 countries, factors such as energy prices, energy taxes and GDP all significantly affect energy intensity of output, whereas Voigt et al. (2014) identify technological changes and sectoral structural factors which explain the trends of energy intensity of output in 40 large economies. Duro (2015) segments countries into several groups and finds that reductions in energy intensity of output often coincide with improvement in inequality. Results from these papers suggest a number of structural factors determine the energy intensity of output.

³ For instance, Jin and Kim (2018) find a long-run relationship between coal consumption and economic growth among non-OECD countries. A higher share of coal consumption inevitably leads to higher CO₂ intensity. Kibria et al. (2019) also identify a non-linear relationship between fossil fuel mix and GDP.

could be one of the reasons why global annual greenhouse-gas emissions increased by 14% between 2008 and 2018.⁴ To achieve the long-term target of reducing total CO₂ emissions while sustaining economic growth, countries have to choose and manage the combinations of fossil fuels and renewables to provide energy by balancing the costs and benefits. In other words, a country selects an “optimal” share of its use of low-emission energy to balance the obligation of reducing CO₂ emissions and the cost saving benefits of using fossil fuels. An optimal share implies that a country adjusts its use of high-emission fuels over time in order to achieve a target level of CO₂ intensity by closing the gap between the actual and target levels. While countries have long-term targets for their total CO₂ emissions under the Paris Agreement, it is not able to identify their respective target CO₂ intensities given the three variables in level 2 of the Kaya formula shown in Figure 1.

The dynamics of CO₂ intensity with adjustment towards a target can be investigated under an approach in the well-established dynamic trade-off theory of firms’ capital structure in the corporate finance literature. The trade-off theory states that firms choose how much debt and how much equity to use by balancing the costs and benefits. Therefore, firms select optimal leverage ratios to balance the dead-weight costs of bankruptcy and the tax saving benefits of debt. The trade-off theory is well supported by both empirical and theoretical studies (see Flannery and Rangan (2006); Graham and Harvey (2001); Robert (2002); Hovakimian et al. (2001); Korajczyk and Levy (2003); Hennessy and Whited (2005); Titman and Tsyplakov (2007); Childs et al. (2005)), and thus remains one of the dominant theories of corporate capital structure. According to their findings, firms that are under- or over-leveraged actively adjust their leverage ratios to narrow the gap between their actual and target leverage ratios. Most firms consider target leverage ratios or ranges when making their debt decisions. In addition, by applying the dynamic partial adjustment model, Flannery and Rangan (2006) find that the realised leverage ratios of different firms adjust towards firms’ respective target leverage ratios

⁴ See Olivier, J. G. J. & Peters, J. A. H. W. Trends in Global CO₂ and Total Greenhouse Gas Emissions (PBL Netherlands Environmental Assessment Agency, 2019).

(which are usually time-varying and determined by the firm's own features). They also find that these target leverage ratios of firms typically vary a lot at different years and across different firms.

This paper uses the dynamic partial adjustment model based on the trade-off theory to investigate whether countries adjust their CO₂ intensities towards targets, and whether financial development of equity markets affects such adjustment. To our best knowledge, this is the first attempt to study countries' CO₂ intensity dynamics and the corresponding adjustment.⁵ The model allows analysing countries' target CO₂ intensities across time by removing the disturbance elements, and also the contribution of representative components underlying the target intensities. In addition, we can further investigate how country-specific characteristics affect the speed of adjustment. The empirical results show that among the 62 studied economies, their actual CO₂ intensities moved towards their targets during the period 1992-2013, albeit there was partial adjustment. Factors such as changes in the fuel mixes from electricity production, economic activities and fossil fuel energy consumption play important roles in determining countries' target CO₂ intensities.

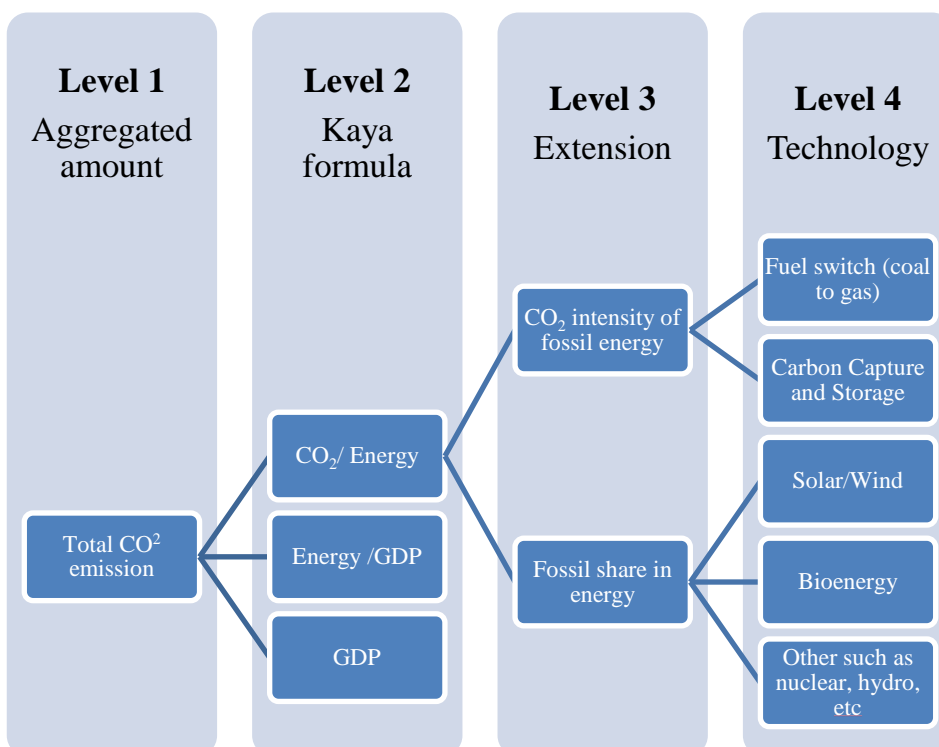
The relation between climate change and the financial sector has been studied to understand how financial development and investments could contribute to climate risk mitigation. For example, Gibson-Brandon and Krueger (2018) show long-term institutional investors invest in assets with a better environmental footprint in their portfolios. Dyck et al. (2019) find a positive relationship between institutional shareholder ownership and firms' environmental and social performance. Shive and Forster (2020) find the relationship between corporate governance and pollution externalities of public and private firms. Hartzmark and Sussman (2019) show substantial net inflows (outflows) into high-sustainability (low-sustainability) US mutual funds when there is a sudden increase in the transparency of the funds' sustainability ratings, suggesting that environmental performance is a positive fund attribute. Kolbel et al. (2018) find direct evidence that investors can affect companies' environmental performance through shareholder engagement, especially when the costs of demanded

⁵ The partial adjustment model is a useful framework to analyse dynamics of an interested variable with target setting, and has also been widely applied in economic literature including governance structure (Wintoki et al. (2012)), risk taking (Calvet et al. (2009)) and R&D intensity (Chen (2018)).

reforms are low. Given such relation, a number of studies address the question how financial development in particular equity markets affects CO₂ emissions. De Haas and Popov (2019) find that deeper stock markets reallocate investment towards industries with lower CO₂ emissions, and allow carbon-intensive industries to reduce their energy intensities. Ilhan et al. (2019) show empirical evidence that among the S&P 500 companies those with higher CO₂ emissions exhibit a higher downside risk as measured by tail risk in their put options. This suggests that stock market participants, particularly institutional investors, assess corporate and financial risks of those companies in high-emission industries. On the other hand, Chava (2014) shows how a better environmental profile of a firm lowers the cost of its equity capital in a sample of US firms. Similarly, Trinks et al. (2017) find that firms with low emissions benefit from cheaper equity in a cross-country data set.

This paper is organised as follows. The dynamic partial adjustment model, including the research questions (hypotheses) and data used for estimations, are discussed in the following two sections respectively. Section 4 presents the empirical results. The effects of financial development on adjustment towards CO₂ intensity targets are illustrated in section 5. The final section concludes.

Figure 1: Key components of the Kaya formula and its extension as shown in Peters et al. (2017).



2. Dynamic partial adjustment model

Countries intend to achieve their target CO₂ intensities. However, adjustment costs may prevent immediate adjustment to a target, as the country trades off its adjustment costs against the costs of adopting suboptimal CO₂ intensity. We estimate a model that permits incomplete (partial) adjustment of the country's initial CO₂ intensity toward its target within each time period. The data can then indicate a typical adjustment speed. We use the partial adjustment model to study whether countries adjust their CO₂ intensities of energy towards targets. The baseline model is specified by the following dynamical panel regression:

$$CI_{i,t} - CI_{i,t-1} = \lambda(CI_{i,t}^* - CI_{i,t-1}) + \delta_t + v_{i,t} \quad , \quad (1)$$

where $CI_{i,t}$ is country i 's current CO₂ intensity, $CI_{i,t}^*$ is country i 's unobserved target CO₂ intensity, δ_t represents the yearly fixed effect and $v_{i,t}$ represents the Gaussian white-noise error component. $(CI_{i,t} - CI_{i,t-1})$ measures the annual change in CO₂ intensity or "intensity adjustment", and $(CI_{i,t}^* - CI_{i,t-1})$ measures the deviation from the target intensity. A country is expected to close a constant proportion λ of the gap between its actual $CI_{i,t}$ and target CO₂ intensities $CI_{i,t}^*$ each year. The parameter λ measures the average speed of adjustments of closing the gap. The parameter is expected to be positive and lie between 0 and 1, such that a larger λ indicates a more rapid speed of adjustment. The specification in Eq.(1) therefore implies that the country's actual CO₂ intensity eventually converges to its target CO₂ intensity $CI_{i,t}^*$.

To yield a testable empirical equation from Eq.(1), we need to make assumptions about the formation of a country's target CO₂ intensity which is unobservable. We assume that a country's target CO₂ intensity is represented by a linear function of various country specific economic and environmental variables $X_{i,t-1}$ and the fixed effect terms η_i^* as follows:

$$CI_{i,t}^* = \beta'X_{i,t-1} + \eta_i^* \quad . \quad (2)$$

$X_{i,t-1}$ includes a set of variables in the extended Kaya formula outlined in Figure 1 and related to CO₂ emissions in the literature (see the discussion in the next section about data). Specifically, we consider the target CO₂ intensity $CI_{i,t}^*$ as a linear function of those variables in the following expression⁶:

$$CI_{i,t}^* = \beta_0 + \beta_1 GDPg_{i,t-1} + \beta_2 \ln(egupp)_{i,t-1} + \beta_3 FF_ENE_{i,t-1} + \beta_4 EP_cs_{i,t-1} + \beta_5 EP_natgs_{i,t-1} + \beta_6 EP_nrs_{i,t-1} + \beta_7 RNET_{i,t-1} + \beta_8 cementsh_{i,t-1} + \eta_i^* \quad (3)$$

where $GDPg$ is a country's rate of real GDP growth, $egupp$ is the energy use (kg of oil equivalent) per \$1000 GDP (constant \$2011 PPP prices), FF_ENE is the fossil fuel energy consumption share, EP_cs is the share of electricity production from coal sources, EP_natgs is the share of electricity production from natural gas sources, EP_nrs is the share of electricity production from nuclear and renewable sources, and $RNET$ is the ratio of net emission transfers, and $cementsh$ is the ratio of CO₂ emission from cement production over the total emission. The first six variables resemble the Kaya-derived indicators⁷, and the last two variables ($RNET$ and $cementsh$) further differentiate countries with a similar rate of GDP growth, but engaging in a different level of carbon-intensive economic activities that are important for CO₂ emissions as shown in Baltagi et al. (2019) and Andrew (2018).

The assumption underlying Eq.(3) suggests that the levels of target CO₂ intensities of energy could be different across countries and over time according to individual countries' "optimal" levels of target CO₂ intensity, based on their current economic and environmental considerations. Given that the variables in Eq.(3) are publicly disclosed information and monitored by international agencies which

⁶ We test the possibility of non-linear relationships by separately adding the squared terms of each of the eight explanatory variables into Eq.(3), but do not find statistically significant squared term for the added variables except for squared term of EP_cs . This suggests that all other seven explanatory variables' relationships with target CO₂ intensities are linear. Regarding EP_cs , the statistical significance of the squared term may potentially capture the feature of the value of EP_cs being bounded. Indeed, based on a simple scatter plot of CO₂ intensities and EP_cs , except around the zero level, the EP_cs displays a quite clear linear relationship with the CO₂ intensities. For model simplicity and easier interpretations, we would keep the linearity assumption in Eq. (3). The results of these additional estimations are available upon request.

⁷ We do not include any variable to represent the carbon capture and storage given that there is little progress made in the past decades as discussed in Peters et al. (2017).

assess the progress of reduction in carbon emissions in individual countries, including peer-group comparison, the coefficients β_n should not be substantially different among countries. Therefore, it is reasonable to assume that there are no heterogeneity coefficients among countries (i.e., similar weights are assigned to these variables by the countries) in Eq.(3).

Finally, we substitute Eq.(3) into Eq.(1) and yield the following regression model:

$$CI_{i,t} = (1 - \lambda)(CI_{i,t-1}) + \lambda(\beta'X_{i,t-1}) + \delta_t + v_{i,t} \quad . \quad (4)$$

We employ the generalised method of moments (GMM) developed by Arellano and Bond (1991) and Blundell and Bond (1998) to estimate the baseline model of Eqs. (1), (3) and (4), as the OLS estimation could lead to biased estimates in the presence of lagged dependent variables and country fixed effects in the regressions.⁸ The GMM approach can also address any potential dynamic panel bias issues for large N, small-T sample. This baseline model is used to test the following hypothesis:

Hypothesis (1): Countries adjust their CO₂ intensities towards targets.

This hypothesis suggests that the partial adjustment with a speed of λ , which is positive but smaller than one, closes the gap between the actual and target CO₂ intensities. According to the trade-off theory, we should observe three important implications from the model, including (i) $\beta' \neq 0$; (ii) $0 < \lambda < 1$; and (iii) variations in the target $CI_{i,t}^*$ is non-trivial (i.e., showing considerable variation across countries and over time).

As the estimation results presented in section 4 support Hypothesis (1) – countries have target CO₂ intensities, we further study the relation between financial development and CO₂ intensities among the countries. Given the accords of lowering CO₂ emissions, we have a conjecture that countries with different degrees of financial development have different upward (U) and downward (D) adjustments towards their CO₂ intensity targets, suggesting that their speeds of adjustments λ_U and λ_D towards targets are not symmetric. In view of the recent emphasis on the role of financial markets

⁸ See Flannery and Hankins (2013) for the discussion of the source of bias in the partial adjustment model and Monte Carlo evidence on how GMM methods can accurately estimate the model.

to mitigate climate change, it is expected that countries with a higher degree of financial development (HFD) have faster speeds of downward adjustment compared with countries with a lower degree of financial development (LFD) to achieve lower CO₂ intensity targets. To test this conjecture, we test the following hypotheses:

Hypothesis (2): All countries have asymmetric speeds of upward- and downward-adjustments towards CO₂ intensity targets, i.e., $H_2: \lambda_D^{All} \neq \lambda_U^{All}$.

Hypothesis (3): Countries with a higher degree of financial development or being an advanced economy, foster faster speeds of adjustment towards CO₂ intensity targets, i.e., $H_3: \lambda^{HFD} > \lambda^{LFD}$.

Hypothesis (4): Countries with a higher degree of financial development have faster downward speeds of adjustment towards CO₂ intensity targets, compared with countries with a lower degree of financial development, i.e., $H_4: \lambda_D^{HFD} > \lambda_D^{LFD}$.

Hypothesis (5): Countries with a higher degree of financial development have slower upward speeds of adjustment towards CO₂ intensity targets, compared with countries with a lower degree of financial development, i.e., $H_5: \lambda_U^{HFD} < \lambda_U^{LFD}$.

Hypothesis (6): Countries with a higher degree of financial development have faster downward than upward speeds of adjustment towards CO₂ intensity targets, i.e., $H_6: \lambda_D^{HFD} > \lambda_U^{HFD}$.

Hypothesis (7): Countries with a lower degree of financial development have faster upward than downward speeds of adjustment towards CO₂ intensity targets, i.e., $H_7: \lambda_U^{LFD} > \lambda_D^{LFD}$.

To test the above hypotheses, we extend the baseline model to five models to analyse (i) whether countries adjust their upward and downward speeds towards CO₂ intensity targets differently, i.e., asymmetric upward and downward adjustments; and (ii) whether, and how, financial development affects countries' speeds of adjustment towards their CO₂ intensity targets. The five extended models are based on the two-stage estimation approach adopted in Faulkender et al.

(2012).⁹ We first estimate Eq.(4) and derive the estimated target $L_{i,t}^*$ backwards using Eq.(3). Then we obtain the deviations from target level $(CI_{i,t}^* - \widehat{CI}_{i,t-1})$ and the actual changes $(CI_{i,t} - \widehat{CI}_{i,t-1})$, which are used to estimate the extended model through the pooled ordinary least squared method with bootstrapped standard errors.

We follow Wright (1976)'s approach to specify the dummy variable for asymmetric responses in handling multiple interaction terms in the following models. To test Hypothesis (2), we introduce model (a) which evaluates asymmetrical responses from possible directional impacts mode as follows:

$$(CI_{i,t} - \widehat{CI}_{i,t-1}) = \lambda_1 (CI_{i,t}^* - \widehat{CI}_{i,t-1})_{L_{i,t}^* - L_{i,t-1} \geq 0} + \lambda_2 (CI_{i,t}^* - \widehat{CI}_{i,t-1})_{L_{i,t}^* - L_{i,t-1} < 0} + \varepsilon_{i,t} . \quad (5)$$

To test Hypothesis (3), we extend model (a) to models (b) and (c) by considering that there is no directional asymmetry, while countries with a higher degree of financial development or being advanced economies have faster speeds of adjustment towards their CO₂ intensity targets compared with the other countries. Models (b) and (c), which test how financial and economic developments affect countries' speeds of adjustment towards CO₂ intensity targets, are specified respectively as follows:

$$(CI_{i,t} - \widehat{CI}_{i,t-1}) = (\lambda + \theta_1 * dum_{FD=1})(CI_{i,t}^* - \widehat{CI}_{i,t-1}) + \alpha_0 * dum_{FD=1} + \varepsilon_{i,t} ; \quad (6)$$

$$(CI_{i,t} - \widehat{CI}_{i,t-1}) = (\lambda + \theta_1 * dum_{AE=1})(CI_{i,t}^* - \widehat{CI}_{i,t-1}) + \alpha_0 * dum_{AE=1} + \varepsilon_{i,t} , \quad (7)$$

where $dum_{FD=1}$ is a dummy variable representing that a country belongs to the higher degree financial development group, while $dum_{AE=1}$ is a dummy variable representing that a country belongs to the advanced economy group. The constructions and definitions of these two dummy variables and time interval for measuring the speeds of adjustment are further discussed in section 3.

⁹ While Dang et al. (2012) develop a one-step approach in estimating similar models, their methodology requires the sample to have a sufficiently large amount of firms, such that the main characteristic of differentiation between groups (regimes) is primarily driven by the threshold variable. Such assumption is obviously not suitable for our country-level sample size.

To test Hypothesis (4) – (7), model (d) assesses asymmetrical responses from directional impacts and how financial development affects the speeds of countries' adjustments towards CO₂ intensity targets. We introduce control variables in model (e) to ascertain the results are not biased from omitted variables. For the control variables $\Delta Z'_t$, we include variables representing the lagged value of total aggregated emission amounts, changes in shares of electricity production from coal sources (EP_cs), nuclear and renewable sources (EP_nrs), and changes in the GDP growth to ensure that any identified faster or slower speeds of adjustment are not derived from unanticipated economical or technological changes. These variables represent effects from episodes such as the shutting-down of nuclear plants or other renewable source power generators, backward switching to coal sources due to price fluctuation or disruptions in access to the relevant resources, economic expansions or recessions. We use these two models to test whether a country with a higher degree of financial development (i.e., more equity-funded markets) contributes to lower CO₂ intensity.¹⁰ To investigate whether financial development and economic development have the same effects on countries' CO₂ intensity dynamics, model (f) replaces the financial development dummy variable with the economic development dummy variable to test the hypothesis. The three models are specified as follows:

Model (d):

$$(CI_{i,t} - \widehat{CI}_{i,t-1}) = (\lambda_1 + \theta_1 * dum_{FD=1})(CI_{i,t}^* - \widehat{CI}_{i,t-1})_{L_{i,t}^* - L_{i,t-1} \geq 0} + (\lambda_2 + \theta_2 * dum_{FD=1})(CI_{i,t}^* - \widehat{CI}_{i,t-1})_{L_{i,t}^* - L_{i,t-1} < 0} + \alpha_0 * dum_{FD=1} + \varepsilon_{i,t} ; \quad (8)$$

Model (e):

$$(CI_{i,t} - \widehat{CI}_{i,t-1}) = (\lambda_1 + \theta_1 * dum_{FD=1})(CI_{i,t}^* - \widehat{CI}_{i,t-1})_{L_{i,t}^* - L_{i,t-1} \geq 0} + (\lambda_2 + \theta_2 * dum_{FD=1})(CI_{i,t}^* - \widehat{CI}_{i,t-1})_{L_{i,t}^* - L_{i,t-1} < 0} + \alpha_0 * dum_{FD=1} + \gamma' \Delta Z'_t + \varepsilon_{i,t} ; \quad (9)$$

¹⁰ We test the robustness by considering the threshold at 30th and 70th percentile. Since the cross-sectional dimension of our sample is relatively small, we do not have sufficient amount of cross-sectional data in all the percentile points to avoid the clustering effect of countries when applying a continuous moderation variable. The results of the sensitivity analysis checking with alternative model specifications are reported in the Appendix.

Model (f):

$$(CI_{i,t} - \widehat{CI}_{i,t-1}) = (\lambda_1 + \theta_1 * dum_{AE=1})(CI_{i,t}^* - \widehat{CI}_{i,t-1})_{L_{i,t}^* - L_{i,t-1} \geq 0} + (\lambda_2 + \theta_2 * dum_{AE=1})(CI_{i,t}^* - \widehat{CI}_{i,t-1})_{L_{i,t}^* - L_{i,t-1} < 0} + \alpha_0 * dum_{AE=1} + \gamma' \Delta Z'_t + \varepsilon_{i,t} \quad (10)$$

The above seven models list all the specifications to test Hypotheses (1) to (7).

3. Data

Our primary data source is the World Bank's World Development Indicators database which annually provides a comprehensive list of indicators on various economic and environmental aspects.¹¹ In this study, we use a sample of 62 economies with the highest CO₂ emission amounts in 2014 and available data for estimations, which are listed in Table 1.¹² The sample period is from 1992 to 2013. The sample starts in 1992 because the first adoption of the United Nations Framework Convention on Climate Change was in May 1992 and the availability of individual country-level data for a batch of countries previously among the disintegrated Soviet Union. The sample period ends in 2014 due to data availability for the CO₂ emissions released by the Carbon Dioxide Information Analysis Centre (CDIAC) which ceased operations in September 2017.

Table 2 presents descriptive statistics for the determinant variables in Eq.(3), including annual data for CO₂ intensity (kg per kg of oil equivalent energy use, denoted as CI), real GDP growth (%), denoted as GDPg), energy use per \$1000 GDP in logarithm (PPP constant 2011, denoted as ln(egupp)), fossil fuel energy consumption (% of total energy consumption, denoted as FF_ene) and electricity productions from coal sources, natural gas sources, and nuclear and renewable sources (% of total denoted as EP_cs, EP_natgs, and EP_nrs)¹³. The actual CO₂ intensity exhibits sizable variations across

¹¹ Data are from <http://datatopics.worldbank.org/world-development-indicators/>

¹² The size of the sample is between Baltagi, et al. (2019)'s 81 countries and De Haas and Popov (2019)'s 48 countries. Overall, the sample covers around 94% of total carbon emissions in 2014.

¹³ We deliberately omit the % shares of electricity production from oil sources, and hydroelectric sources in Eq.(3) to avoid the issue of multi-collinearity. The interpretation of these coefficients is discussed in Section 4.

the sample, with a mean value of 2.417 and standard deviation of 0.593. Variations of CI across countries and over time also exist, which are likely to be explained by country-specific characteristics.

To gauge the possible impact of the determinant variables on CI, we first split the sampled countries into two groups according to their CO₂ intensity above the upper 75th and below the lower 25th percentiles at each time point. The average values of the variables in Eq.(3) for the two groups are plotted in respective panels of Figure 2. The differences of the average values of the variables between the two groups are in general persistent over time. We expect GDPg (Panel A), FF_ene (Panel B), and EP_cs (Panel C) to be positively related to CI, given that their values for the upper 75th group are higher than those for the lower 25th group. Such expectations are consistent with intuitions of the positive relationships of carbon intensities with economic growth and use of fossil fuels. EP_nrs (Panel E) is negatively related to CI, given that nuclear and renewable energy has low carbon emissions.¹⁴ Panel D does not indicate a clear sign for the EP_natgs. As natural gas has relatively less CO₂ emissions, EP_natgs is expected to be negatively related to CI. As shown in Panel H, energy use per unit of GDP (ln(egupp)) does not show a clear relationship with energy intensity consistent with no intuitive argument to support their relationship.

To better understand the effects of international trade on countries' CO₂ emissions, Peters et al. (2011) develop an annual trade-linked global database to quantify the growth in CO₂ emissions transfers via trade activities for 119 countries. Their work highlights a key economic dimension of carbon emission transfers, which warrants monitoring in addition to countries' own territorial emissions. We define the ratio of net emission transfers (RNET) as:

¹⁴ Although Baltagi et al. (2019) are able to capture more variables in their proposed semiparametric panel data model, their objective is to indicate the strong relationship between carbon emissions per capita and GDP elasticity after controlling for a vast amount of possible concepts. Furthermore, their statistically significant variables closely resemble our choice of variables in determining the target CO₂ intensity. Different from Baltagi et al. (2019) in presenting only the shares of electricity production from nuclear and hydroelectric powers sources, we introduce shares of electricity production from coal sources, natural gas sources and nuclear plus other renewable sources for two reasons. First, the changes in coal and natural gas in electricity production can better represent the impacts on CO₂ intensity from shifting away from more carbon-intensive fossil fuel to a lesser one. Second, the share of electricity production from hydroelectric power sometimes has a counter-intuitive sign in the estimations for CO₂ intensity, since the higher share for a country is associated with a lower technological level of a country, which is difficult to quantify and control for. Dummy variables also cannot be included in our system-GMM estimation with the country fixed effect approach.

$$\text{RNET} = \frac{\text{Territorial Emissions} - \text{Consumption Emissions}}{\text{Consumption Emissions}}, \quad (11)$$

representing the degree of emission transfers, such that a country with a positive RNET is a net CO₂ emission importer which produces goods with CO₂ emission within the country's own territory, and exports the goods to other countries for consumption. A country with a negative RNET is the other way round. The RNET is more relevant to CO₂ intensity compared with the trade openness (trade value/GDP) indicator, as trade openness does not differentiate types of goods and services by their levels of CO₂ emissions while they are represented by the same trade value. We expect a positive relationship between the RNET and CO₂ intensity as shown in Panel F since the country will take on the role to export carbon-intensive products to another country, thus absorbing the emission into its own territory.

Regarding the role of cement production in carbon emission, Andrew (2018) assembles various sources to present a comprehensive analysis of global CO₂ emissions from cement production, including a number of large economies with a significant presence in the global industry. Indeed, cement production is considered to be CO₂ emission intensive relative to other manufacturing industries. In particular, the process of making 'clinker' emits a large amount of CO₂ in addition to the emissions due to energy consumed in the process of thermal production. The variable *cementsh* is measured as the ratio of emission from cement production to the total emission from a country.¹⁵ As shown in Panel G, we expect the variable *cementsh* is positively related to CO₂ intensity.

To test Hypotheses (2) to (7) using the second stage regression specifications, we employ the International Monetary Fund (IMF)'s classifications and databases to construct the dummy variables for measuring countries' relative standings in economic development and financial market development. In measuring a country's degree of financial development, we use financial development indices developed in Svirydzenka (2016). Through summarising and extending the results of previous literature¹⁶, Svirydzenka (2016) constructs nine individual indices and one

¹⁵ The breakdown information is available from CDIAC's by-component reporting.

¹⁶ For instance, Beck et al. 1999, Levine 2002 and Chiak et al. 2012.

aggregated index, covering 183 countries annually from 1980 to 2013 (and extended to 2017 in updates), for characterising their financial institutions and financial market developments in dimensions including depth, access, and efficiency. In view of the finding of De Haas and Popov (2020) that more developed equity markets led to lower CO₂/GDP, we employ the financial market development index to identify the degree of financial development, and divide the countries in the sample into two groups: countries' current degree of financial development larger (smaller) than the median at each time point are categorised in the high (low) degree of financial development group with the dummy variable $dum_{FD} = 1$ ($dum_{FD} = 0$). For the grouping of the state of economic development, we adopt the IMF's method by classifying them into the advanced economy group and the developing economy group according to the IMF's World Economic Outlook October 2019 issue (IMF, 2019) with the dummy variable $dum_{AE} = 1$ for the advanced economy group and $dum_{AE} = 0$ for the developing economy group. We consider a longer time interval in evaluating the speeds of adjustment. In particular, we set the time interval to be 3 years (starting from 1995 and until 2013) to maximise the number of time points in the sample. The longer time interval helps to mitigate impacts from misspecification of the target level for individual years, if any.¹⁷ In addition, we marginally round up the deviations from the target level $(CI_{i,t}^* - \widehat{CI}_{i,t-1})$ to 0.03 if the calculated value is between (0, 0.03) and round it down to -0.03 if the calculated value is between (-0.03, 0) respectively.

¹⁷ We exclude two countries (Singapore and Venezuela) from our second stage estimation because their CO₂ intensity series fluctuate wildly arising from reporting issues. This may affect the estimation of speeds of adjustment.

Table 1: Sampled economies and their respective CO₂ emission (in kilo metric tons) in 2014.

Rank in 2014	country	kilo metric tons	Rank in 2014	country	kilo metric tons
1	CHINA (MAINLAND)	2806634	34	PAKISTAN	45350
2	USA	1432855	37	PHILIPPINES	28812
3	INDIA	610411	39	CZECH REPUBLIC	26309
4	RUSSIAN FEDERATION	465052	40	NIGERIA	26256
5	JAPAN	331074	42	BELGIUM	25457
6	GERMANY	196314	43	COLOMBIA	22932
7	IRAN	177115	44	CHILE	22515
8	SAUDI ARABIA	163907	45	BANGLADESH	19959
9	SOUTH KOREA	160119	46	ROMANIA	19090
10	CANADA	146494	48	GREECE	18358
11	BRAZIL	144480	49	ISRAEL	17617
12	SOUTH AFRICA	133562	50	BELARUS	17316
13	MEXICO	130971	51	PERU	16838
14	INDONESIA	126582	53	MOROCCO	16325
15	UNITED KINGDOM	114486	54	AUSTRIA	16011
16	AUSTRALIA	98517	56	SINGAPORE	15373
17	TURKEY	94350	57	NORWAY	12988
18	ITALY	87377	58	FINLAND	12899
19	THAILAND	86232	60	HKSAR	12605
20	FRANCE	82704	61	PORTUGAL	12286
21	POLAND	77922	62	ECUADOR	11977
23	KAZAKHSTAN	67716	63	SWEDEN	11841
24	MALAYSIA	66218	64	BULGARIA	11567
25	SPAIN	63806	65	HUNGARY	11477
26	UKRAINE	61985	68	AZERBAIJAN	10223
27	UAE	57641	69	SWITZERLAND	9628
28	ARGENTINA	55638	72	NEW ZEALAND	9453
29	EGYPT	55057	74	DENMARK	9135
30	VENEZUELA	50510	77	SLOVAKIA	8366
32	NETHERLANDS	45624	78	TUNISIA	7862
33	VIETNAM	45517	79	JORDAN	7213

Source: Tom Boden and Bob Andres (Oak Ridge National Laboratory); Gregg Marland (Appalachian

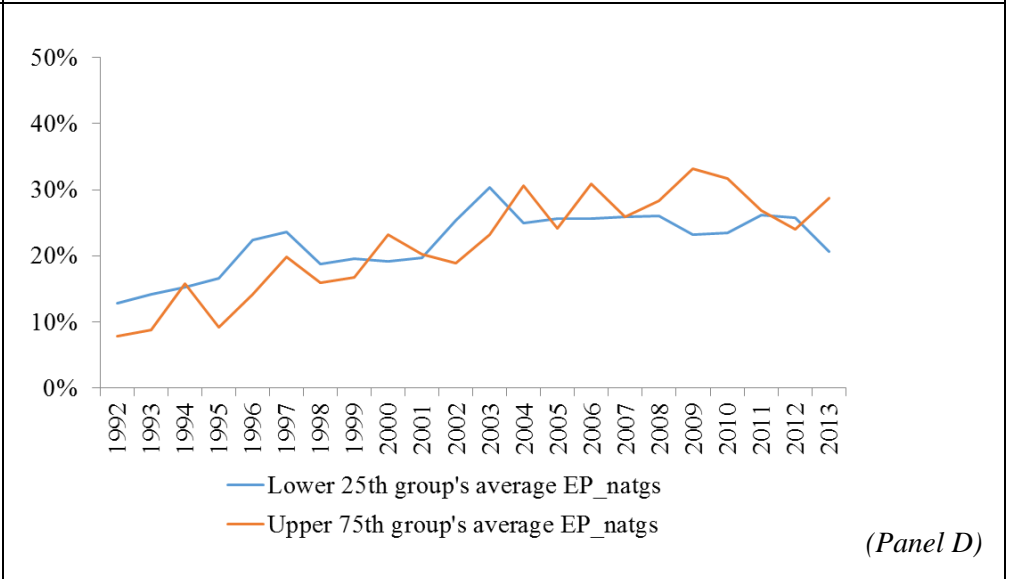
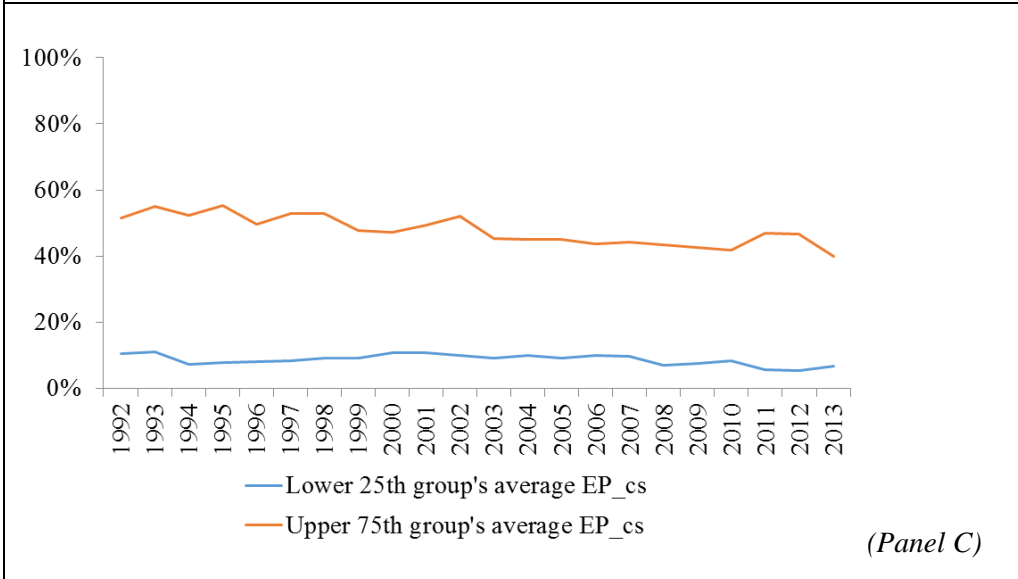
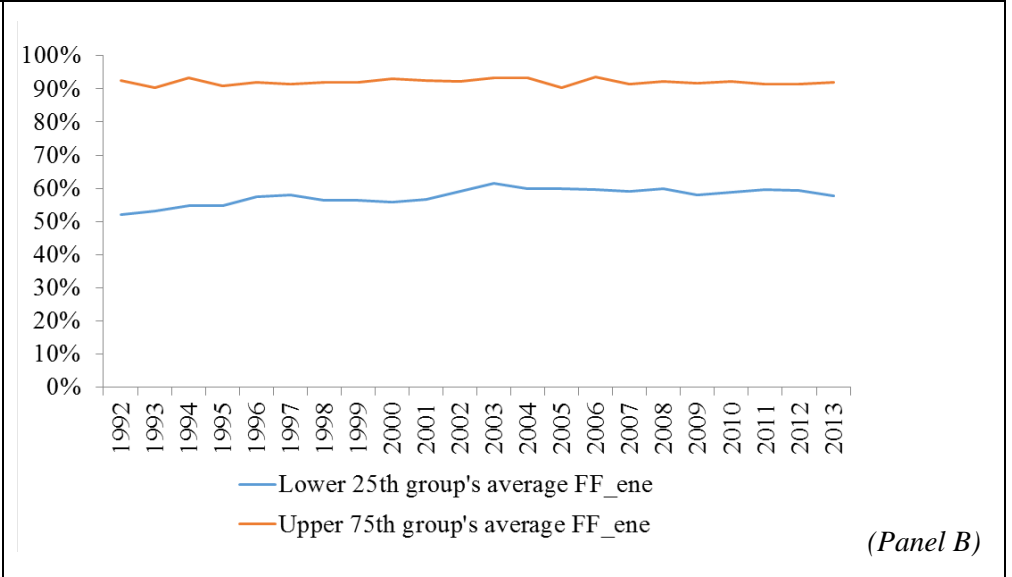
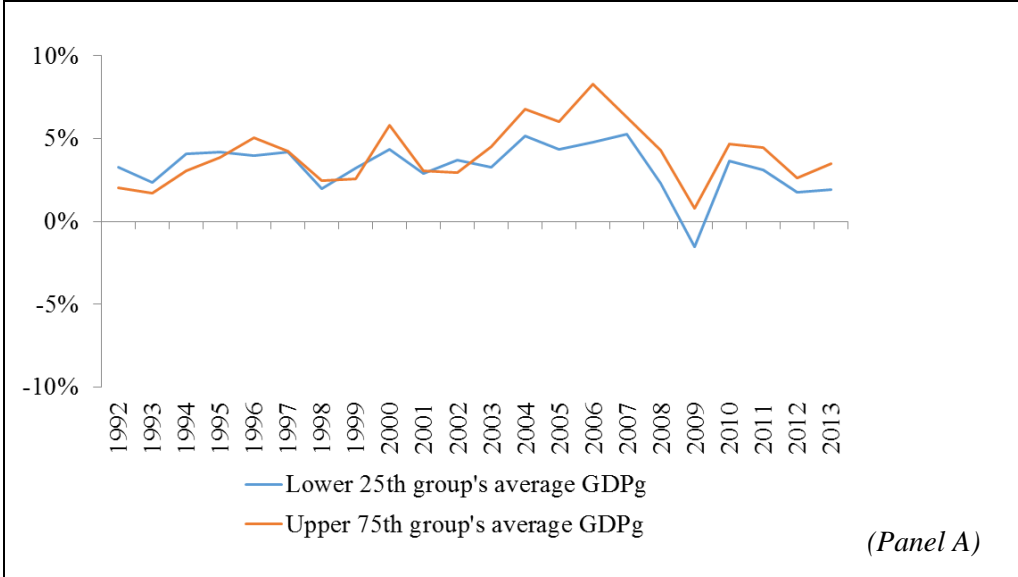
State University) DOI: 10.3334/CDIAC/00001_V2017

Table 2: Descriptive statistics of determinant variables.

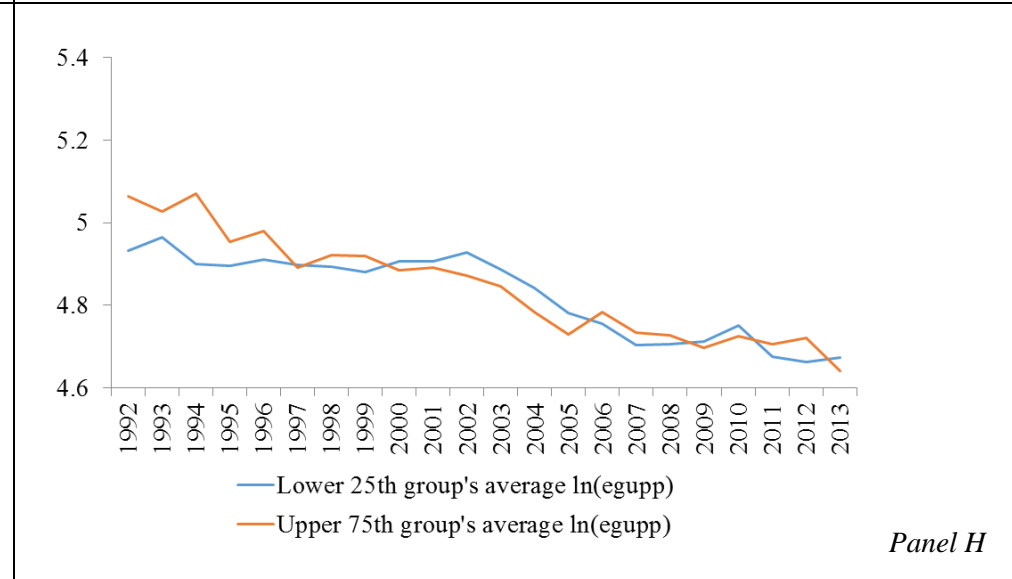
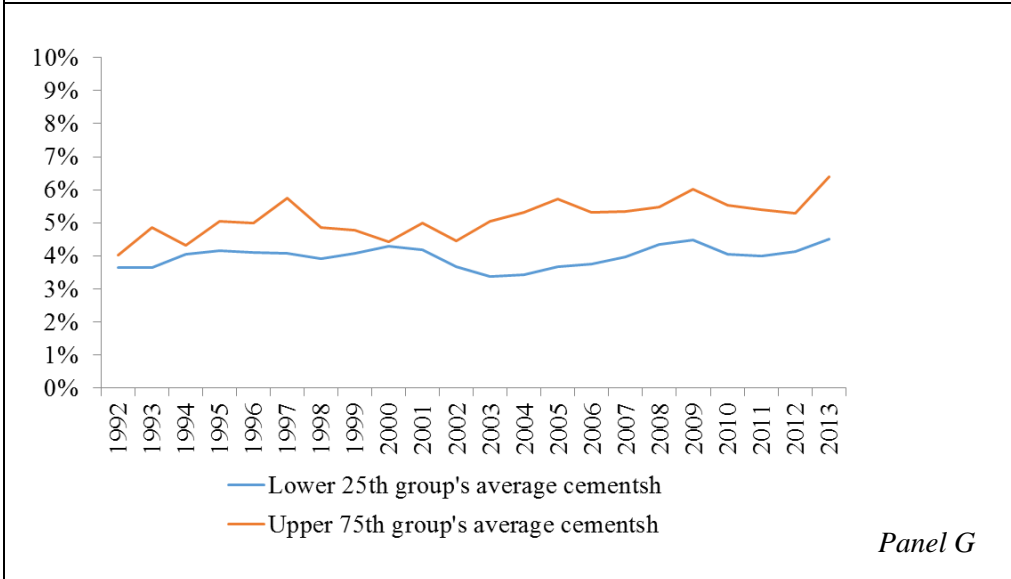
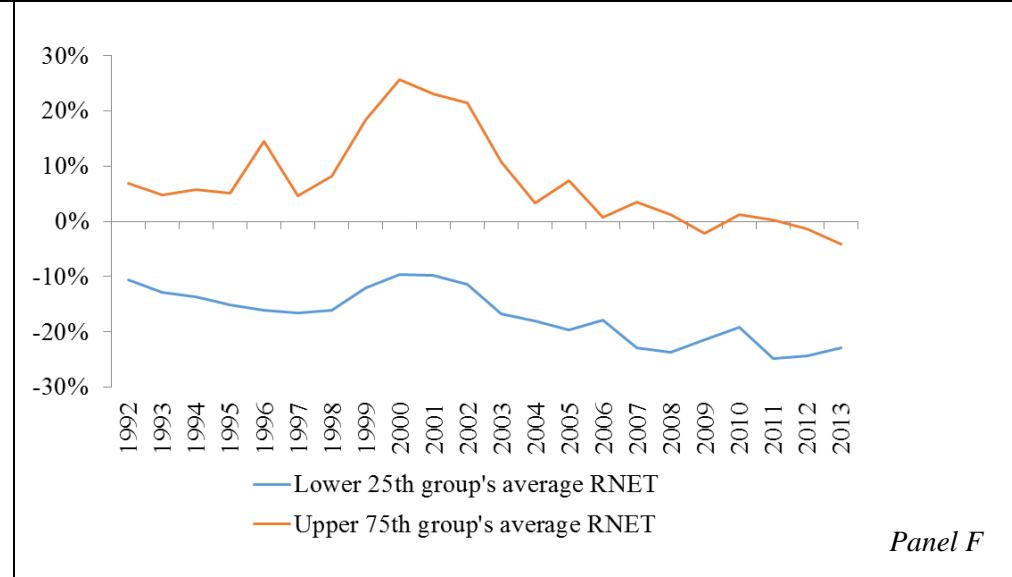
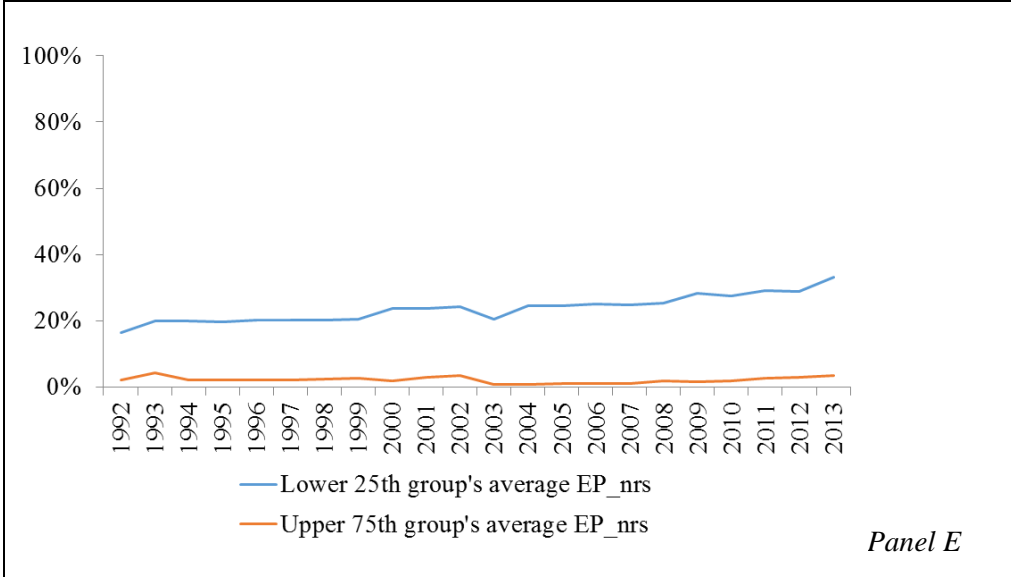
Variable	No. of Obs.	Mean	S.D.	Median	Max	Min
CI	1364	2.4174	0.5928	2.4404	3.9296	0.4735
GDPg	1363	0.0337	0.4320	0.0356	0.3446	-0.231
ln(egupp)	1364	4.8455	0.4391	4.7793	6.4603	3.6263
FF_ene	1364	0.7927	0.1715	0.8390	0.9999	0.1585
EP_cs	1364	0.2588	0.2736	0.1753	0.9799	0
EP_natgs	1364	0.2736	0.2679	0.1804	0.9903	0
EP_nrs	1364	0.1361	0.1862	0.0374	0.8303	0
RNET	1364	-0.04151	0.2796	-0.0716	2.600	-0.7974
cementsh	1364	0.0443	0.0343	0.0346	0.1949	0

Source: World Development Indicator database, Peters et al. (2011) and Andrew (2018).

Figures 2-1: Average values of explanatory variables in upper 75th percentile and lower 25th percentile groups of countries according to their CO₂ intensity (CI).



Figures 2-2: (Cont.)



4. Results of dynamic partial adjustment of CO₂ intensity towards targets

Table 3 presents the regression results obtained from the baseline specification in Eq.(4). We adopt a gradual approach by putting the relevant representative variables at each level of the extended Kaya formula to check the stability of coefficient estimates. In column (1), we include the variables in the basic Kaya formula including the GDP growth (GDPg) and energy use per GDP (energy intensity, egupp) only. The result indicates a certain degree of partial adjustment of the CO₂ intensity, while only the GDP growth has a positively significant impact. It is estimated that a country on average closes approximately 40% (speed of adjustment λ) of the gap between its actual and target CO₂ intensity levels in one year. Countries with a higher GDP growth rate (particularly developing economies) usually have to support their growth engine through higher consumption and production, thus having higher energy demand. Given that fossil fuels are more readily available to satisfy the energy demand in terms of cost and time for power plant construction compared to other renewable resources, countries with high GDP growth exhibit higher CO₂ intensity. The estimations for the energy intensity (energy/GDP) in the Kaya formula are insignificant in all the regressions, suggesting that the energy intensity does not have directional relation with a country's CO₂ intensity, consistent with the findings in Duro (2015) and Camarero et al. (2013).

Columns (2) and (3) of Table 1 show that the coefficients of the energy sources including the fossil fuel energy consumption share (FF_ene), shares of electricity production (EP_cs) and share of electricity production from nuclear and renewable sources (EP_nrs), are significant and their associated signs are consistent with the intuitions and previous studies including Dogan and Seker (2016), Zhu et al. (2014), Balogh and Jám bor (2017) and Baltagi et al. (2019). While the sign of the share of electricity production from natural gas sources (EP_natgs) is consistent with intuition, it is not statistically significant. With the presence of FF_ene in Eq.(3), EP_cs and EP_natgs can be interpreted respectively as the relative intensiveness of CO₂ emission embedded in the types of fossil fuel being used in energy consumption. A higher EP_cs represents the use of more CO₂-intensive source, while

higher EP_natgs reflects the use of lower CO₂ emittance fossil fuels, both relative to the oil source. The GDP growth remains significant.

Column (4) further includes the ratio of net emission transfers arising from international trade activities (RNET) and the ratio of CO₂ emissions from cement production over the total emission (cementsh) into the dynamic partial adjustment model. Both RNET and cementsh are significantly and positively related to the CO₂ intensity. The result indicates that countries adjust their CO₂ intensities lower towards targets by transferring their high carbon-intensive economic activities away through importing goods from producing countries as noted in Knight and Schor (2014) and Hasanov et al. (2018). However, on aggregate such transfers through trades do not mitigate CO₂ emissions globally. Indeed, higher values of cement production over the total emission (cementsh) give higher target CO₂ intensities. Consistent with previous studies, including Worrell et al. (2001), Kim and Worrell (2002), and Xu et al. (2012), which discuss the extent of CO₂ emissions generated by the cement industry from global or selected large economies' perspectives, the regression results here demonstrate that countries with higher emissions from the share of cement production tend to have higher CO₂ intensities. The share of electricity production from natural gas sources (EP_natgs) becomes statistically significant under column (4) specification including the variables (RNET) and (cementsh).

The annual speeds of adjustment λ are statistically significant and consistently lie within the range of 0.38 to 0.48 across the specifications considered in columns (1) to (4). The estimations suggest that countries close 38% to 48% of the gaps between their actual and target CO₂ intensities in one year. The results support Hypothesis (1) that countries have CO₂ intensity targets and adjust their CO₂ intensities towards the targets over time. Figure 3 shows the average actual and target CO₂ intensities and their standard deviations among the countries in the sample. The left panel demonstrates that the actual and estimated target CO₂ intensities follow similar downward trends on the average of the sample countries. This suggests progress in the use of lower emission energy sources and the development of industries with lower carbon emissions. The gradual declines in their

standard deviations reflect that differences in the shares of the use of high-emission fuels among countries have reduced over time. The results are consistent with the intuition that individual countries observe their obligations under the Kyoto Protocol with long-term and sustained reductions in their CO₂ intensities. Looking ahead, a continuous sign of downward trends in countries' CO₂ intensities towards their targets may be an early indicator reflecting progress in countries moving to low-emission energy and renewables, and choosing "optimal" (target) shares in their use of low-emission energy, subject to the obligation of reducing CO₂ emissions.

To ensure that the signs and statistical significance of the proposed variables in the estimations are not driven primarily by the system-GMM estimation approach, column (5) shows the standard fixed-effect panel estimation for comparison. The variables except EP_cs have the same signs and statistical significance as in the system-GMM estimation approach.¹⁸ While the coefficient of EP_cs becomes positively insignificant, the absolute magnitudes of the coefficients of EP_natgs and EP_nrs increase. Such a result may be due to collinearity among these three variables of shares of electricity production from different energy sources. To further test whether the results in column (4) of Table 4 are sensitive to countries' economic status, we re-estimate Eq.(4) by dividing the sample into two sub-groups, namely the emerging economy group and the advanced economy group plus large CO₂ emissions emerging economies. The results are reported in Appendix I.

As discussed in Flannery and Rangan (2006), if individual countries' targets are estimated validly in the partial adjustment model, we should see that countries on average adjust (at least in a partial sense) their CO₂ intensities towards their targets over time. Nevertheless, adjustment in an overall sense may mask the poor fitting of countries' actual and target CO₂ intensities individually. To address this issue, we estimate the model for six selected countries, namely China, France, Germany, India, Japan and the US across the sample period and show qualitatively that the movements in their target CO₂ intensities reasonably describe those of the actual CO₂ intensities. The target CO₂ intensity

¹⁸ The fixed effect regression in column (5) report a high R² of around 91%, suggesting that the variables captured in our specification can explain a significantly large portion of the variation in CO₂ intensity.

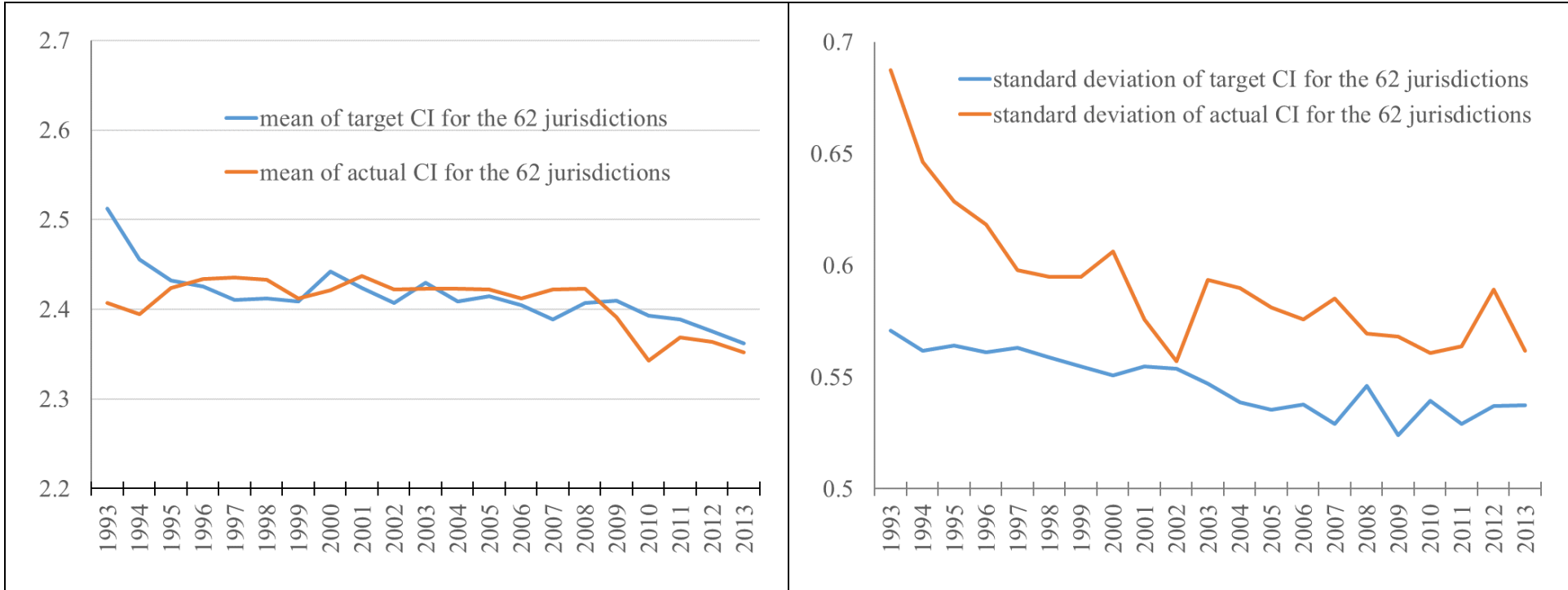
movements also fit those countries' specific developments discussed in the literatures and reports. While the estimated targets are not set out by countries, the results show that the actual and target CO₂ intensities of the countries have similar levels and trends over time. The results are available on request.

Table 3: Regression results for the partial adjustment model in baseline specification.

	(1)	(2)	(3)	(4)	(5)
Estimation approach	System-GMM	System-GMM	System-GMM	System-GMM	Fixed effect
Variable					
CI (t-1)	0.5975*** (0.1118)	0.6191*** (0.0975)	0.5530*** (0.0923)	0.5159*** (0.0798)	0.4601*** (0.0358)
GDPg (t-1)	0.4134* (0.2411)	0.4791** (0.2006)	0.4265** (0.1854)	0.3198** (0.1464)	0.4060** (0.1552)
ln(egupp) (t-1)	-0.0277 (0.0674)	-0.0235 (0.0393)	-0.0278 (0.0294)	-0.0279 (0.0218)	-0.0376 (0.0351)
FF_ene (t-1)		1.1067*** (0.2971)	1.041*** (0.2858)	1.1397*** (0.2388)	1.2490*** (0.2038)
EP_cs (t-1)			0.2785*** (0.0695)	0.2875*** (0.0522)	0.0306 (0.0768)
EP_natgs (t-1)			-0.1093 (0.0744)	-0.1611*** (0.0600)	-0.1914*** (0.0583)
EP_nrs (t-1)			-0.2901*** (0.0793)	-0.1623*** (0.0554)	-0.3638** (0.1488)
RNET (t-1)				0.1858*** (0.0378)	0.1196*** (0.0277)
cementsh (t-1)				2.0125*** (0.4325)	1.5280** (0.6134)
Observations (adjusted)	1177	1171	1171	1171	1176
no. of countries	62	62	62	62	62
Yearly fixed effect	Y	Y	Y	Y	Y
Country fixed effect	Y	Y	Y	Y	Y
No. of instruments	35	41	59	71	n.a.
P-value of Arellano Bond test for AR(2)	0.495	0.527	0.477	0.345	n.a.
P-value of Hansen test for over-identifying restrictions	0.18	0.394	0.542	0.909	n.a.
Speed of adjustment	0.4025***	0.3809***	0.447***	0.4841***	n.a.
Overall R ²	n.a.	n.a.	n.a.	n.a.	0.915

Clustered (by country) robust standard errors are reported in the brackets. ***, ** and * represented statistical significance at the 1%, 5% and 10% levels respectively. By employing the system GMM approach, we have adopted the “xtabond2” command developed by Roodman (2009) in STATA, and utilized the small sample biased-corrected two-step estimation option. To address the problem of too many instruments, we also utilized the “collapse” option and further restricted the number of IVs used up to the past 3 (4) lags for level equations (difference equations).

Figure 3: Mean and standard deviations of actual vs target CO₂ intensities among the 62 economies.



5. Effects of financial development on adjustment towards CO₂ intensity targets

Table 4 presents the results of the six extended specifications (Eqs. 5-10) testing Hypotheses (2) - (7). In the first column, we study the overall speed of adjustment towards the CO₂ intensity targets among all sampled countries in the three-year interval time as the referencing point. The result suggests that countries close 44% of the gap between their target and actual CO₂ intensities in one year, which is comparable to the results in Table 3. The results of model (a) in the second column show the asymmetrical responses, where countries have a faster upward adjustment towards targets than downward adjustment. However, the difference in the speeds of adjustment is not significant. The Wald test indicates that the null hypothesis of no difference between the speeds of upward and downward adjustments among countries cannot be rejected at the 10% confidence level. Therefore, there is no evidence to reject the null of Hypothesis (2) (i.e., $H_2: \lambda_D^{All} = \lambda_U^{All}$), suggesting that countries as a whole do not have different upward and downward adjustment speeds towards their CO₂ intensity targets.

The results of model (b) in the third column report that a higher degree of development in financial markets does not contribute to faster speeds of adjustment towards the target CO₂ intensities. Similarly, regarding the advanced/developing economy group, the results in the fourth column for model (c) show that countries in the advanced economy group display signs of having slower adjustment speeds than those in the developing economy group. Therefore, the results of models (b) and (c) do not support Hypothesis 3 that countries with a higher degree of financial development or being advanced economies have faster speeds of adjustment towards CO₂ intensity targets (i.e., $H_3: \lambda^{HFD} > \lambda^{LFD}$ or $H_3: \lambda^{AE} > \lambda^{non-AE}$). Additional information in model (c) is that the dummy variable for the advanced economy group is negative and significant at the 5% confidence level, suggesting that the advanced countries reduce their CO₂ intensities. The result is consistent with Mielnik and Goldemberg (1999)'s finding that developed countries are decarbonising.

The results of model (d) in Table 5 indicate some signs of asymmetric upward and downward speeds of adjustment for the countries with higher degrees of financial development as shown by the two interaction terms of the dummy variables. To check the robustness of the results, we include the control variables in model (e) to capture the effect of other factors on the target CO₂ intensities as described in section 2. The results of model (e) show that the two interaction terms with downward and upward adjustments become statistically significant at the 5% and 10% levels respectively. Regarding the downward adjustment, countries with a higher degree of financial development close 55.2% of the gap between the actual and target CO₂ intensity, about 27.4% larger than their counterparts. On the other hand, for the upward adjustment, countries with a higher degree of financial development only close 26.9% of the gap, about 33.7% smaller than their counterparts. The results support Hypotheses (4) and (5): Countries with a higher degree of financial development have faster (slower) downward (upward) speeds of adjustment towards CO₂ intensity targets, than those of countries with a lower degree of financial development, i.e., $H_4: \lambda_D^{HFD} > \lambda_D^{LFD}$; ($H_5: \lambda_U^{HFD} < \lambda_U^{LFD}$).

We employ the one-sided z-test (χ^2 -test) to evaluate Hypotheses (4) to (7), given that both the signs and the magnitudes of heterogeneity are important. However, it is well-known that the one-sided z-test (χ^2 -test) may suffer from weaker statistical significance, therefore, we further employ the individual or joint two-sided tests to confirm that the speeds of adjustment between the two groups are heterogeneous at higher than the 10% significance level before we proceed to evaluate the one-sided test. Table 6 reports the statistics and p-values of the estimations for Hypotheses (4) to (7) by either z-test or χ^2 -test with the null hypotheses. The null hypotheses of the one-sided z-test (χ^2 -test) are the opposite cases of those specified in Hypotheses (4) to (7). The one-sided test suggests that the null hypotheses are rejected at the 5% or 10% significance level, supporting Hypotheses (4) to (7). The results indicate that countries with a higher degree of financial development, on average, have faster (slower) downward (upward) speeds of adjustment than their counterparts, supporting $H_4: \lambda_D^{HFD} > \lambda_D^{LFD}$; ($H_5: \lambda_U^{HFD} < \lambda_U^{LFD}$). From an individual country perspective, countries which belong to the

higher (lower) degree of financial development group have faster (slower) downward speeds of adjustment than upward speeds of adjustment, supporting $H_6: \lambda_D^{HFD} > \lambda_U^{HFD}$; ($H_7: \lambda_U^{LFD} > \lambda_D^{LFD}$).

We estimate model (f) to check whether the effect of financial market development can be explained simply by the relative higher degree of economic development among the countries. As shown in the last column of Table 5, both interaction terms become statistically insignificant, demonstrating that the interaction effect from a higher degree of financial development cannot be replicated by using the advanced economy group.

In summary, by applying the partial adjustment model to study the CO₂ intensity dynamics, we find no evidence supporting Hypotheses (2) and (3), but evidence supporting Hypotheses (4) to (7). The results show that there are no systemic differences between upward and downward adjustment speeds towards CO₂ intensity targets among all economies in the sample. The countries with a higher degree of financial development do not have higher speeds of adjustment. However, countries with a higher degree of financial development in terms of equity markets have faster (slower) downward (upward) speeds of adjustment towards CO₂ intensity targets, compared with those of countries with a lower degree of financial development. Consistently, countries with a higher (lower) degree of financial development have faster (slower) downward than upward speeds of adjustment towards their targets. These findings are in line with recent studies on the interactions between financial markets and climate change. De Haas and Popov (2019) find that more financially developed countries are associated with lower CO₂ emissions per capita. Koellner et al. (2012) show that equity funds managed according to sustainability goals exhibit better environmental ratings, fewer damages and environmental impacts. Flammer (2020) indicates that the issuance of “green” bonds improves the environmental performance of firms.

Table 4: Asymmetric responses by directional or group characteristics.

	Model (baseline)	Model (a)	Model (b)	Model (c)
	Pooled OLS	Pooled OLS	Pooled OLS	Pooled OLS
Dummy group			Higher financial market development	Advanced economy group
<i>Dependent variables</i>	DEV_actual (t)	DEV_actual (t)	DEV_actual (t)	DEV_actual (t)
<i>Explanatory Variable</i>				
DEV_target (t)	0.440*** (0.047)		0.441*** (0.060)	0.463*** (0.060)
DEV_target # (Dummy =1)			-0.014 (0.097)	-0.105 (0.086)
DEV_target_up (t) (>=0)		0.489*** (0.093)		
DEV_target_down (t) (<=0)		0.401*** (0.094)		
Dummy =1			-0.037*** (0.014)	-0.035** (0.014)
Observations (adjusted)	359	359	359	359
Yearly fixed effect	Yes	Yes	Yes	Yes
Bootstrap replications	1000	1000	1000	1000
Adjusted R ²	0.3046	0.3039	0.3145	0.3144
P-value of H0:				
Coef(DEV_target_up)		0.59		
=				
Coef(DEV_target_down)				

Bootstrapped standard errors are reported in the brackets. ***, ** and * represented statistical significance at the 1%, 5% and 10% levels respectively. We have also alternatively tested for the clustered-by-country robust standard errors and white-robust standard errors. Overall, the statistical significances for the 2nd stage regressions hold at the 10% level and therefore implications from these results still apply. The results using alternative types of standard errors are available upon request.

Table 5: Asymmetric response with interaction from group characteristics

	Model (d)	Model (e)	Model (f)
	Pooled OLS	Pooled OLS	Pooled OLS
Dummy group	Higher financial market development	Higher financial market development	Advanced economy group
<i>Dependent variables</i>	DEV_actual (t)	DEV_actual (t)	DEV_actual (t)
<i>Explanatory Variable</i>			
DEV_target_up (t) (≥ 0)	0.600*** (0.117)	0.606*** (0.128)	0.534*** (0.120)
DEV_target_up # (Dummy =1)	-0.314* (0.168)	-0.337** (0.171)	-0.265 (0.184)
DEV_target_down (t) (≤ 0)	0.302*** (0.113)	0.278** (0.112)	0.398*** (0.113)
DEV_target_down # (Dummy =1)	0.238 (0.170)	0.274* (0.152)	0.060 (0.142)
Dummy =1	0.011 (0.025)	0.027 (0.024)	0.003 (0.020)
Δ GDP_g (t)		1.467** (0.598)	1.609*** (0.604)
Δ EP_cs (t)		0.704** (0.347)	0.590* (0.344)
Δ EP_nrs (t)		-1.059*** (0.373)	-1.071*** (0.356)
$\ln(\text{TotCEMamount}) (t-1)$	-0.008 (0.005)	-0.010* (0.005)	-0.010** (0.005)
Observations (adjusted)	359	359	359
Yearly fixed effect	Yes	Yes	Yes
Bootstrap replications	1000	1000	1000
Adjusted R ²	0.3235	0.3687	0.3587

Bootstrapped standard errors are reported in the brackets. ***, ** and * represented statistical significance at the 1%, 5% and 10% levels respectively. We have also alternatively tested for the clustered-by-country robust standard errors and white-robust standard errors. Overall, the statistical significances for the 2nd stage regressions hold at the 10% level and therefore implications from these results still apply. The results using alternative types of standard errors are available upon request.

Table 6: Hypothesis testing results for asymmetrical speeds of adjustment

Null hypothesis	Two-sided test	One-sided test*
H2	$\lambda_D^{AU} = \lambda_U^{AU}$	/
χ^2 -stat	0.29	
p-value	0.590	
H3	$\lambda^{HFD (AE)} = \lambda^{LFD (non-AE)}$	/
z-stat	-0.14 (-1.22)	
p-value	0.888 (0.224)	
H4	$\lambda_D^{HFD} = \lambda_D^{LFD}$	$\lambda_D^{HFD} \leq \lambda_D^{LFD}$
z-stat	1.8	
p-value	0.0725	0.036
H5	$\lambda_U^{HFD} = \lambda_U^{LFD}$	$\lambda_U^{HFD} \geq \lambda_U^{LFD}$
z-stat	-1.96	
p-value	0.0495	0.025
H6	$\lambda_D^{HFD} = \lambda_U^{HFD}$	$\lambda_D^{HFD} \leq \lambda_U^{HFD}$
χ^2 -stat	2.59	
p-value	0.1074	0.054
H7	$\lambda_D^{LFD} = \lambda_U^{LFD}$	$\lambda_D^{LFD} \geq \lambda_U^{LFD}$
χ^2 -stat	2.46	
p-value	0.1169	0.058
	Joint tests of H6&H7 (two-sided)	
χ^2 -stat	4.88	/
p-value	0.0871	/

Note: The one-sided and two-sided z-test (χ^2 -test) results are based on the bootstrapped standard errors from models (a), (b), (c) and (e). The null hypotheses of the one-sided z-tests (χ^2 -test) are the opposite cases of Hypotheses (2) to (7) respectively such that the alternative hypotheses are the same as those stated in Hypotheses (2) to (7).

6. Conclusion

Using the dynamic partial adjustment model based on the trade-off theory of firms' capital structure in corporate finance, we find that economies adjust their CO₂ intensities towards targets based on the sample covering 62 economies from 1992 to 2013. They adjust their CO₂ intensities towards their optimal levels on the use of low-emission energy to trade off their obligation of reducing CO₂ emissions against the cost saving benefits of using high-emission fuels. Countries with a higher (lower) degree of financial development have faster (slower) downward than upward speeds of adjustment towards their CO₂ intensity targets. Consistently, countries with a higher (lower) degree of financial market development have faster (slower) downward than upward speeds of adjustment towards their targets. Such findings are, however, not associated with the state of economic development. After controlling for the cross-country differences in macro-economic and environmental factors, our analysis suggests that financial development in terms of equity markets is an essential factor for the CO₂ reduction. More developed and deeper financial markets could reallocate investment towards cleaner energy and attract energy-intensive industries to use low-emission energy resulting in reducing CO₂ intensity.

Indeed, a sign of emerging downward trends in CO₂ intensity is an early indicator of progress in moving to low-emission energy and renewables, and without necessarily slowing GDP growth. Given the analysis showing that countries adjust their CO₂ intensities towards targets, these targets should be part of the toolkit available to governments when making CO₂ emission policies. If set correctly, and with proper financial development, these targets can lead to absolute reductions in CO₂ emissions by creating incentives for energy efficiency and the development of clean energy technologies through reallocating investment towards those technologies and higher levels of R&D-related direct investment.

Appendix I: Sub-sample analysis on estimation of equation (4) by economic status

In this appendix I, we aim to test whether the formulation of target equation (Eq.(3)) will be significantly different for countries in different economic status. Specifically, we test if the coefficients from estimating Eq.(4) will result in changes in signs or become quantitatively irrelevant if we restrict the sample to emerging economy group only (total number of countries: 36) versus advanced economy group plus nine important emerging economies only (total number of countries: 36). We reported the subsample results of stage 1 equation by i.) emerging economy group only and ii.) advanced economy group plus nine large CO₂ emitter emerging economies in Table A1.

The results of the coefficients in Column (1) and (2) both show that the signs are consistent across the full sample and the two sub-samples. The magnitude of the sub-sample estimation using only the emerging economy group (slightly more than half of the full sample) is in fact quite close to the full sample estimation. The signs of coefficients for AE plus large EME are qualitatively similar to those in the full sample, but the magnitude and statistical significance for some variables (including electricity production from natural gas and electricity production from nuclear and renewable sources) weakens. This may be due to the fact that the advanced economies may have employed a mix of two sources as strategies to displace coal and oil source, which make these two variables less distinguishable from each other. Despite these relatively minor quantitative changes, the results from the two subsample regressions suggest that these explanatory variables are important determinants for a country's carbon intensity adjustment, as suggested by the theory in Sections 1 and 2.¹⁹

¹⁹ We also test whether the results will substantially differ by removing a small number of countries (potential outliers). In short, we find that the statistical significance of several variables weakens when some countries are dropped out (up to 4 countries in various settings) but the signs and magnitudes of coefficients remain largely stable. These additional estimations are available upon request.

Table A5: Subsample analysis for the partial adjustment model in baseline specification according to the economic status of the economies

	(0) Reference	(1)	(2)
Subsample	Full Sample	EME group	AE group plus 9 large EMEs
L.depvar_int	0.516*** (0.080)	0.554*** (0.103)	0.559*** (0.090)
L.lnegupp	-0.028 (0.022)	0.005 (0.024)	-0.056 (0.046)
L.GDPg	0.320** (0.146)	0.453 (0.293)	0.410 (0.458)
L.ff_ene	1.140*** (0.239)	1.119*** (0.273)	0.964*** (0.215)
L.EP_cs	0.287*** (0.052)	0.246*** (0.086)	0.339*** (0.093)
L.EP_nats	-0.162*** (0.055)	-0.156** (0.069)	-0.099 (0.060)
L.EP_nrs	-0.161*** (0.060)	-0.197* (0.110)	-0.086* (0.042)
L.r_et_ce	0.186*** (0.038)	0.178*** (0.052)	0.192** (0.077)
L.co2cement	2.013*** (0.433)	2.296*** (0.810)	1.662*** (0.570)
Constant	0.296** (0.124)	0.044 (0.167)	0.429 (0.258)
Speed of adjustment	0.484***	0.446***	0.441***
No. of countries	62	36	36
Yearly fixed effect	Y	Y	Y
Country fixed effect	Y	Y	Y

Cluster-robust standard errors are reported in the brackets. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels respectively. All estimation is using the same specifications as the baseline specification but only results of interest are presented here.

Appendix II: Sensitivity of model (e) results to alternative specifications

We study the impact of alternative specifications in the second stage regression of model (e) as a sensitivity checking exercise. Specifically, we study the impact of the results with the following changes in the model specification: (i) we choose different thresholds to construct the higher and lower financial development groups; (ii) remove observations with large actual deviations; and (iii) segment the higher and lower degree of financial development groups of countries with the sub-category indexes proposed by Svirydzenka (2016). Overall, the results indicate consistent signs of the interaction impacts with the financial development dummy variable, although the magnitudes and statistical significances mostly weaken.

The first three columns in Table A2 present the sensitivity of the results for changes in the threshold to identify the group with a higher degree of financial development by checking the results from setting the threshold at the 30th and 70th percentiles. The upward dampening effect of this group in general holds and remains statistically significant, whereas the downward accelerating effect is also maintained, but the statistical significance weakens. We also test whether the result is driven by some outliers by removing the observations of the actual dynamics higher than +/- 0.3 levels in the three-year interval time and re-running the regression of model (e) in column 4 (trimmed). While both the statistical significance and magnitude of the speed of adjustment weaken, the signs of the interaction terms do not change, suggesting that the asymmetrical interaction responses are not primarily driven by the outliers.

The last three columns in Table A2 show the results by replacing the financial market development index with each of the individual financial market characteristic indexes using different percentile thresholds.²⁰ Overall, none of the individual indexes completely replicate the results as

²⁰ We check the results with the threshold setting mostly at the 50th percentile (with the efficiency index using the 65th percentile) to ensure that we do not include too many countries in the group with a higher degree of financial development, while very few countries are in the other group. We present selected results of which the asymmetrical speed of adjustment maintains at similar magnitudes with model (e) in Table 4.

those using the aggregated index, although the market depth and market efficiency indexes display faster downward adjustment, similar to the aggregated financial market development index.

Table A2: Selected results on the sensitivity of results of model (e) to different specifications

Group Identifier	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Financial Market Development Index	Financial Market Development Index	Financial Market Development Index	Financial Market Development Index (Trimmed)	Financial Market Index (measured by Depth)	Financial Market Index (measured by Access)	Financial Market Index (measured by Efficiency)
	50th percentile	30th percentile	70th percentile	50th percentile	50th percentile	50th percentile	65th percentile
Estimation method	Pooled OLS	Pooled OLS	Pooled OLS	Pooled OLS	Pooled OLS	Pooled OLS	Pooled OLS
DEV_target_up (t) (>=0)	0.606*** (0.128)	0.592*** (0.166)	0.551*** (0.111)	0.426*** (0.081)	0.592*** (0.123)	0.615*** (0.133)	0.602*** (0.126)
DEV_target_up # (Dummy_upp =1)	-0.337** (0.171)	-0.156 (0.209)	-0.325* (0.183)	-0.250** (0.109)	-0.322* (0.172)	-0.300* (0.178)	-0.369** (0.169)
DEV_target_down (t) (<=0)	0.278** (0.112)	0.298* (0.167)	0.383*** (0.104)	0.189** (0.080)	0.344*** (0.125)	0.371*** (0.126)	0.371*** (0.106)
DEV_target_down # (Dummy_upp =1)	0.274* (0.152)	0.151 (0.193)	0.122 (0.157)	0.161 (0.107)	0.135 (0.165)	0.071 (0.163)	0.161 (0.167)
Dummy_upp =1	0.027 (0.024)	0.017 (0.032)	0.016 (0.021)	0.003 (0.016)	0.019 (0.023)	0.035 (0.023)	0.023 (0.022)
No. of observations	359	359	359	336	359	359	359
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bootstrap replications	1000	1000	1000	1000	1000	1000	1000

Bootstrapped standard errors are reported in the brackets. ***, ** and * represent significance at the 1%, 5% and 10% levels respectively. Control variables in model (e) are included in the specifications but their coefficients are not reported here.

References

- Andrew, R. M., 2018. "Global CO₂ emissions from cement production". *Earth System Science Data*. 10. 195-217.
- Arellano, M. and Bond, S., 1991. "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations," *Review of Economic Studies*, Oxford University Press, vol. 58(2), pages 277-297.
- Balogh, J.M., and Jám bor, A., 2017. "Determinants of CO₂ Emission: A Global Evidence," *International Journal of Energy Economics and Policy*, Econjournals, vol. 7(5), pages 217-226.
- Baltagi, B.H., et al., 2019. "Carbon Dioxide Emissions and Economic Activities: A Mean Field Variational Bayes Semiparametric Panel Data Model with Random Coefficients," *Annals of Economics and Statistics*, GENES, issue 134, pages 43-77.
- Beck, T., et al., 1999. "A new database on financial development and structure," Policy Research Working Paper Series 2146, The World Bank.
- Blanco, G., et al., 2014. *Climate Change 2014: Mitigation of Climate Change, Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* (ed. Edenhofer et al.) (Cambridge, UK: Cambridge University Press) pp 351–411.
- Blundell, R. and Bond, S., 1998. "Initial conditions and moment restrictions in dynamic panel data models," *Journal of Econometrics*, Elsevier, vol. 87(1), pages 115-143, August.
- Calvet, L. E., et al., 2009. "Fight or Flight? Portfolio Rebalancing by Individual Investors," *The Quarterly Journal of Economics*, Oxford University Press, vol. 124(1), pages 301-348.
- Camarero, M., et al., 2013. "Are the determinants of CO₂ emissions converging among OECD countries?" *Economics Letters*, Elsevier, vol. 118(1), pages 159-162.
- Chava, S., 2014. Environmental Externalities and Cost of Capital. *Management Science* 60(9), 2223-2247.
- Chen, Y., 2018. "Partial Adjustment Toward Target R&D Intensity." *R& D Management*. 48. 591-602. 10.1111/radm.12320.
- Childs, P., et al. (2005). "Interactions of corporate financing and investment decisions: The effects of agency conflicts." *Journal of Financial Economics*, 76, 667-690

- Cihak, M., et al., 2012. "Benchmarking financial systems around the world," Policy Research Working Paper Series 6175, The World Bank.
- Dang, V.A., et al., 2012. "Asymmetric capital structure adjustments: New evidence from dynamic panel threshold models," *Journal of Empirical Finance*, Elsevier, vol. 19(4), pages 465-482.
- De Haas, R. and Popov, A., 2019. "Finance and carbon emissions," Working Paper Series 2318, European Central Bank.
- Dogan, E. and Seker, F., 2016. "Determinants of CO₂ emissions in the European Union: The role of renewable and non-renewable energy," *Renewable Energy*, Elsevier, vol. 94(C), pages 429-439.
- Duro, J.A., 2015. "The international distribution of energy intensities: Some synthetic results," *Energy Policy*, Elsevier, vol. 83(C), pages 257-266.
- Dyck, A., et al., 2019. Do Institutional Investors Drive Corporate Social Responsibility? International Evidence. *Journal of Financial Economics* 131, 693-714
- Faulkender, M., et al., 2012. "Cash flows and leverage adjustments," *Journal of Financial Economics*, Elsevier, vol. 103(3), pages 632-646.
- Flammer, C., 2020. "Corporate Green Bonds." Manuscript, Boston: Boston University. Available at SSRN: <https://dx.doi.org/10.2139/ssrn.3125518>
- Flannery, M. J. and Rangan, K. P., 2006. "Partial adjustment toward target capital structures," *Journal of Financial Economics*, Elsevier, vol. 79(3), pages 469-506, March.
- Flannery, M. J. and Hankins, K.W., 2013. "Estimating dynamic panel models in corporate finance," *Journal of Corporate Finance*, Elsevier, vol. 19(C), pages 1-19.
- Feng, K., et al., 2015. "Drivers of U.S. CO₂ emissions 1997-2013," *Nature Communications*. 6. 10.1038/ncomms8714.
- Filipović, S., et al., 2015. "Determinants of energy intensity in the European Union: A panel data analysis," *Energy*, Elsevier, vol. 92(P3), pages 547-555.
- Gibson-Brandon, R. and Krueger, P., 2018. "The Sustainability Footprint of Institutional Investors." ECGI Working Paper No. 571

- Graham, J. and Harvey, C., 2001. "The theory and practice of corporate finance: evidence from the field." *Journal of Financial Economics* 60, 187–243.
- Hartzmark S. M., and Sussman, A. B., 2019. "Do Investors Value Sustainability? A Natural Experiment Examining Ranking and Fund Flows," *Journal of Finance*, vol. 74(6), pages 2789-2837.
- Hasanov, F. J., et al., 2018. "The impact of international trade on CO₂ emissions in oil exporting countries: Territory vs consumption emissions accounting," *Energy Economics*, Elsevier, vol. 74(C), pages 343-350.
- Herzog, T., et al., 2006. "Target: Intensity. An Analysis of Greenhouse Gas Intensity Targets." World Resources Institute, ISBN 978-1569736388.
- Hennessy, C. A., and Whited, T. M., 2005. "Debt Dynamics," *Journal of Finance*, 60(3),1129-1165.
- Hovakimian, A., et al., 2001. "The debt-equity choice: an analysis of issuing firms." *Journal of Financial and Quantitative Analysis*, 36, 1–24.
- Ilhan, E., et al., 2019. "Carbon Tail Risk". mimeo.
- IMF, 2019. World Economic Outlook, October 2019 Issue. USA: International Monetary Fund.
- Jin, T., and Kim. J., 2018. "Coal Consumption and Economic Growth: Panel Cointegration and Causality Evidence from OECD and Non-OECD Countries," *Sustainability*, MDPI, *Open Access Journal*, vol. 10(3), pages 1-15, March.
- Kibria, A., et al., 2019. "Fossil fuel share in the energy mix and economic growth," *International Review of Economics & Finance*, Elsevier, vol. 59(C), pages 253-264.
- Kim, Y. and Worrell, E., 2002. "CO₂ Emission Trends in the Cement Industry: An International Comparison," *Mitigation and Adaptation Strategies for Global Change*, Springer, vol. 7(2), pages 115-133, June.
- Knight, K. and Schor, J., 2014. "Economic Growth and Climate Change: A Cross-National Analysis of Territorial and Consumption-Based Carbon Emissions in High-Income Countries." *Sustainability*. 6. 3722-3731. 10.3390/su6063722.
- Kölbel, J. et al. 2018. "Beyond Returns: Investigating the Social and Environmental Impact of Sustainable Investing". SSRN Electronic Journal. 10.2139/ssrn.3289544.

- Koellner, T., et al., 2007. “Environmental Impacts of Conventional and Sustainable Investment Funds Compared Using Input-Output Life-Cycle Assessment,” *Journal of Industrial Ecology*, Yale University, vol. 11(3), pages 41-60, July.
- Korajczyk, R., and Levy, A., 2003. “Capital structure choice: macroeconomic conditions and financial constraints.” *Journal of Financial Economics*, 68, 75–109.
- Le Quéré, et al., 2019. “Drivers of declining CO₂ emissions in 18 developed economies.” *Nature Climate Change*. 9. 213-217. 10.1038/s41558-019-0419-7.
- Levine, R., 2002. “Bank-Based or Market-Based Financial Systems: Which Is Better?”, *Journal of Financial Intermediation*, Elsevier, vol. 11(4), pages 398-428, October.
- Lima, F., et al. 2016. “A cross-country assessment of energy-related CO₂ emissions: An extended Kaya Index Decomposition Approach,” *Energy*, Elsevier, vol. 115(P2), pages 1361-1374.
- Mielnik, O. and Goldemberg, J., 1999. “The evolution of the ‘carbonization index’ in developing countries.” *Energy Policy*. 27. 307-308. 10.1016/S0301-4215(99)00018-X.
- Nakicenovic, N. 1997. “Decarbonization as a long-term energy strategy”, *Environment, energy, and economy: strategies for sustainability* (eds. by Kaya, Y. and Yokoburi, K) Tokyo: United Nations Univ. Press. ISBN 9280809113.
- Peters, G.P., et al., 2011. “Growth in emission transfers via international trade from 1990 to 2008.” *Proceedings of the National Academy of Sciences* 108, 8903-8908. (Data has been updated and extended to year 2014).
- Peters, G. P., et al. 2017. “Key indicators to track current progress and future ambition of the Paris Agreement.” *Nature Climate Change* 7, 118–122. <https://doi.org/10.1038/nclimate3202>
- Raupach, M. R., et al., 2007. “Global and regional drivers of accelerating CO₂ emissions.” *Proceedings of the National Academy of Sciences USA* 104, 10288-10293.
- Roberts, M., 2002. “The dynamics of capital structure: an empirical analysis of a partially observable system.” Duke Working paper.
- Roodman, D., (2009), “How to do xtabond2: An introduction to difference and system GMM in Stata”, *Stata Journal*, 9, issue 1, p. 86-136,

- Shive, S., and Forster, M., 2020. "Corporate governance and pollution externalities of public and private firms", *Review of Financial Studies*, vol. 33 (3), 1296–1330.
- Steckel, J. C., et al. 2015. "Drivers for the renaissance of coal." Proceedings of the National Academy of Sciences USA 112, E3775-E3781 (2015).
- Svirydzhenka, K., 2016. "Introducing a New Broad-based Index of Financial Development," IMF Working Papers 16/5, International Monetary Fund. (Data has been updated and extended to year 2017).
- Titman, S., and Tsyplakov, S., 2004. "A dynamic model of optimal capital structure." *Review of Finance*, 11(3), 401–451.
- Trinks, A., et al., 2017. "Carbon Intensity and the Cost of Equity Capital". mimeo.
- Voigt, S., et al., 2014. "Energy intensity developments in 40 major economies: Structural change or technology improvement?". *Energy Economics*, 41, 47-62.
- Wintoki, M. B., et al., 2012. "Endogeneity and the dynamics of internal corporate governance," *Journal of Financial Economics*, Elsevier, vol. 105(3), 581-606.
- World Bank. 2019, World Development Indicators. Available from: <http://www.databank.worldbank.org/data/reports.aspx?source=worlddevelopment-indicators>.
- Worrell, E., et al. 2001. "Carbon Dioxide Emission from the Global Cement Industry". Annual Review of Energy and the Environment. 26. 303-29. 10.1146/annurev.energy.26.1.303.
- Wright, G. C. 1976. "Linear Models for Evaluating Conditional Relationships." *American Journal of Political Science* 2:349–373.
- Xu, J., et al., 2012. "Energy consumption and CO₂ emissions in China's cement industry: A perspective from LMDI decomposition analysis". *Energy Policy*. 50. 821–832. 10.1016/j.enpol.2012.08.038.
- Zhu, Z.S., et al., 2014. "The differences of carbon intensity reduction rate across 89 countries in recent three decades," *Applied Energy*, Elsevier, vol. 113(C), pages 808-815