Centre for Climate Change Economics and Policy

Grantham Research Institute on Climate Change and the Environment

Emissions-GDP Relationship in Times of Growth and Decline

Baran Doda

June 2013

Centre for Climate Change Economics and Policy
Working Paper No. 136

Grantham Research Institute on Climate Change and the Environment

Working Paper No. 116

The Centre for Climate Change Economics and Policy (CCCEP) was established by the University of Leeds and the London School of Economics and Political Science in 2008 to advance public and private action on climate change through innovative, rigorous research. The Centre is funded by the UK Economic and Social Research Council and has five inter-linked research programmes:

1. Developing climate science and economics
2. Climate change governance for a new global deal
3. Adaptation to climate change and human development
4. Governments, markets and climate change mitigation
5. The Munich Re Programme - Evaluating the economics of climate risks and opportunities in the insurance sector

More information about the Centre for Climate Change Economics and Policy can be found at: http://www.cccep.ac.uk.

The Grantham Research Institute on Climate Change and the Environment was established by the London School of Economics and Political Science in 2008 to bring together international expertise on economics, finance, geography, the environment, international development and political economy to create a world-leading centre for policy-relevant research and training in climate change and the environment. The Institute is funded by the Grantham Foundation for the Protection of the Environment and the Global Green Growth Institute, and has five research programmes:

1. Global response strategies
2. Green growth
3. Practical aspects of climate policy
4. Adaptation and development
5. Resource security

More information about the Grantham Research Institute on Climate Change and the Environment can be found at: http://www.lse.ac.uk/grantham.

Emissions-GDP Relationship in Times of Growth and Decline

Baran Doda [*][†]

June 2013

Grantham Research Institute on Climate Change and the Environment
London School of Economics and Political Science

Abstract

This empirical paper focuses on the relationship between changes in GDP and CO_2 emissions as a country's economy moves through periods of growth and decline. Using a comprehensive panel, I document substantial heterogeneity in the relationship across countries. Specifically, countries can be classified into one of the following three groups. Group D (for decline) includes countries where the emissions growth rate is more strongly associated with the GDP growth rate in periods of GDP decline than in periods of GDP growth. Group G (for growth) includes countries where the degree of association is stronger in periods of GDP growth. Finally, in group S (for symmetrical) it is not possible to reject the hypothesis that the relationship is the same for growth and decline. According to a simple count criterion, approximately a third of the countries in the sample fall into each group. Notably, China and the US, currently the world's largest emitters by a substantial margin, are in group D. These results have potentially important consequences for long-term emissions projections. They also suggest that macroeconomic stabilization policies may have adverse emissions consequences by limiting the cleansing effect of periods in which GDP declines.

[*]L.B.Doda@lse.ac.uk

[†]I thank Alex Bowen and Jonathan Colmer for several insightful conversations, and seminar participants at the Global Green Growth Institute (GGGI) for their comments. I also gratefully acknowledge the financial support of the GGGI. The usual disclaimer applies.

1 Introduction

The relationship between emissions and GDP as the economy moves through periods of economic growth and decline has received increasing attention since the onset of the Great Recession. The topic is relevant for climate change policy because it determines in part the future emissions paths associated with projected GDP paths. Policy makers may also be interested in knowing how their macroeconomic stabilization policies will affect emissions. In an environment where climate change policies are hotly debated, the popular media are peppered with articles on how the Great Recession initially led to a decline in global emissions in 2009, which has since been more than reversed.[1] There is also a small but growing empirical and theoretical literature that touches upon the topic from a real business cycle perspective.

The current paper makes a contribution to this debate by focusing on a particular aspect of the relationship between emissions and GDP, namely whether the relationship is different in periods of economic growth than in periods of decline. My empirical strategy is to identify the strength of this relationship using a flexible fixed effects specification in a comprehensive panel covering the period between 1950 and 2011. The specification is flexible in the sense that two separate slope coefficients corresponding to periods of GDP growth and decline are estimated for each country in the sample. The high level result is that there is substantial cross country heterogeneity. I show that ignoring this heterogeneity can lead to misleading results.[2]

More specifically, the countries in the sample can be classified into one of the following three groups. Group D (for decline) includes countries where the relationship is asymmetrical in the sense that emissions growth rate is more strongly associated with GDP growth rate in periods of economic decline relative to periods of economic growth. Group G (for growth) includes countries where the relationship is asymmetrical in the opposite direction, i.e. the degree of association is stronger in periods of economic expansion. Finally, in group S (for symmetrical) it is not possible to reject the hypothesis that the relationship is the same.

How are countries distributed across these distinct groups? According to a simple count criterion approximately a third of the countries in the sample fall into each group. Moreover, each group contains countries that are diverse according to relevant criteria such as developed versus developing, large versus small economy/population, energy exporting versus importing, etc. These points are illustrated in Table 1 which shows the world's top twenty emitters in 2009 and their respective groups. The key message emerging from the table, and indeed from the paper, is that there is substantial cross-country heterogeneity in the way emissions and GDP are related in periods of growth and decline. Accounting for this heterogeneity has potentially important policy implications.

In order to see why, notice that the asymmetry in the relationship across periods of growth versus decline induces a path dependency for emissions. Consequently, when faced with identical GDP

[1] See, for example, BBC (2010), Financial Times (2009), Huffington Post (2012), and Wall Street Journal (2010).
[2] See the discussion of York (2012) below and in section 4.

dynamics over a given time horizon, the emissions of a group G country will exhibit a greater relative increase than the emissions of a group D country. This is because in group G countries a smaller portion of emissions added in periods of growth are removed in periods of decline. As a simple numerical example in section 5 shows, this can be quantitatively significant. In response to the same stylized GDP path, which features 22% growth over 15 years, emissions decline by 5% in the typical group D country while they increase by 26% in the typical group G country. Put differently, starting from the same initial GDP and emissions level, the cumulative emissions of the group G country is 13.5% greater than the group D country.

Moreover, the same asymmetry has an additional and related implication for how the macroeconomic stabilization policies impact long run emissions in different countries. In particular, a lower standard deviation of output implies lower (higher) long run emissions in group G (D) countries. Continuing with the numerical example, a 9% reduction in the standard deviation of GDP changes the 5% decline in the long run emissions of the typical group D country to a 4% increase. Conversely, the 26% increase in the group G country emissions declines to a 17% increase. In other words, macroeconomic stabilization policies can make long run emissions targets easier to achieve in group G countries, but harder in group D countries.

There is a small but growing academic literature which focuses on the emissions and climate-change implications of economic growth. York (2012) is a recent paper that is closely related. It is also motivated by the strong implicit assumption of symmetry in the relationship between emissions and GDP. The author tests the assumption empirically by estimating an econometric specification with separate slope and intercept coefficients for periods of economic growth and decline using annual World Bank data. He finds that the assumption of symmetry is rejected because the relationship between emissions and GDP is stronger during periods of economic growth relative to decline. In the language of this paper, the main conclusion of York (2012) is that the typical country behaves like a group G country. I argue below that this conclusion is not valid, and demonstrate that it is driven by the strong implicit assumption of cross-country homogeneity and questionable econometric choices.

Other empirical papers that analyze the co-evolution of emissions and GDP include Peters et al (2012), Jotzo et al (2012) and Doda (2012). The former two are in essence case studies of the response of emissions to GDP dynamics in the aftermath of the Great Recession. Doda (2012), on the other hand, provides a statistical analysis of emissions-GDP relationship at business cycle frequencies in a wide and long panel. Using a macroeconomic strategy common in the real business cycle literature, the paper establishes a number of stylized facts after decomposing emissions and GDP into their growth and cyclical components using the Hodrick-Prescott filter. The main conclusions are that the time series for the cyclical component of emissions is more volatile than that for the cyclical component of GDP, and that the series are positively correlated for a vast majority of the countries in his sample. Moreover, emissions become less volatile and the correlation coefficient between the two series becomes greater for countries with a higher GDP per capita. The results of Doda (2012) are relevant for the current paper in that they show heterogeneity across countries is an important feature of the data.

Two recent papers on related topics push the research frontier along the theoretical dimension. The main research question in Heutel (2012) is how optimal abatement policies respond to business cycle fluctuations induced by shocks to total factor productivity. Fischer and Springborn (2011) study the implications of alternative policy instruments (i.e. a cap, a tax or an intensity target) on levels and volatilities of macroeconomic variables in a real business cycle environment. Both papers calibrate their models to the US. The sensitivity of their results to various aspects of cross-country heterogeneity, such as the asymmetry highlighted here, remains unexplored.

The rest of the paper is organized as follows. The next section describes the data I use. In section 3, I describe my empirical approach, and provide and discuss the estimation results. A robustness analysis is in Section 4. The relevance of these results for policy are covered in section 5. Section 6 concludes.

2 Data

CO_2 emissions and GDP are the variables of interest in this paper. They are denoted $emis_{it}$ and gdp_{it} where subscript i and t indicate country and year respectively. $emis_{it}$ is from Boden et al (2011) at the Carbon Dioxide Information Analysis Center (CDIAC) of Oak Ridge National Laboratory in the US. CDIAC maintains one of the most reliable, comprehensive and current databases with long time series for CO_2 emissions for all countries of the world. While the main database contains observations up to and including 2009, preliminary estimates for several key emitters are also available for 2010 and 2011. I include these in my sample. $emis_{it}$ is expressed in million metric tons of carbon.

The GDP data comes from the Conference Board (2013) Total Economy Database, which provides data from 1950 onwards for most countries in the world. More specifically, gdp_{it} is the total GDP, measured in millions of 1990 US$ which are converted using Geary Khamis PPPs.

The focus in this paper is on the relationship between *changes* in emissions and GDP. Consequently, I concentrate on the first differences of the natural logarithm of each variable defined as

$$\begin{aligned} \Delta lemis_{it} &= log(emis_{it}) - log(emis_{it-1}) \\ \Delta lgdp_{it} &= log(gdp_{it}) - log(gdp_{it-1}) \end{aligned}$$

There are 122 countries for which data exist for all or some of the period covering 1950-2011, and 6174 country-year observations. In this unbalanced panel, there are 48 countries with data for 60 years or more and 97 countries with data for 40 years or more. Those 25 countries with less than 40 years of data are primarily ex-communist countries. Table A1 in the appendix lists these countries along with a few relevant characteristics such as the start year, number of observations and the number of periods in which a decline in GDP is observed.

Before proceeding to present my empirical strategy and results, I describe two restrictions I impose in the rest of the paper. First, I exclude extreme outliers in the distribution of $\Delta lemis_{it}$ by dropping those observations that are more than 5 standard deviations away from the overall mean of this variable. This implies that I drop 25 *country-year observations* which are positive outliers and 10 *country-year observations* which are negative outliers.[3] The restriction is innocuous in the sense that the results are broadly the same for non-outlier countries when the restriction is not imposed.

The second restriction I impose is that for a country to be included in the estimation sample, it needs to have experienced at least 3 periods of GDP decline over the sample period. There are twelve countries which fail to meet this condition. Pakistan and Yemen do not experience declines in GDP at all, whereas Bangladesh, Colombia, Egypt, Slovakia and Slovenia experience only one. In Armenia, Australia, Bosnia and Herzegovina, Norway and Taiwan GDP declines only in two years. After imposing these two restrictions, the model described in the following section is estimated using a sample made up of 110 countries and 5668 country-year observations.

3 Empirical Strategy and Results

My empirical strategy is to run a flexible fixed effects regression in the panel described above. I use the term flexible to indicate the fact that for each country I estimate two separate slope coefficients corresponding to periods of GDP growth and decline. In particular, I estimate

$$\Delta lemis_{it} = \alpha + \alpha^D D_{it} + \sum_i \beta_i \Delta lgdp_{it} + \sum_i \beta_i^D D_{it} \Delta lgdp_{it} + \gamma_t + \alpha_i + \varepsilon_{it} \qquad (1)$$

where D_{it} is a dummy variable that takes the value 1 if there is a decline in GDP in country i and period t. The coefficients of interest are β_i and β_i^D which summarize the relationship between changes in emissions and GDP. A key advantage of Equation (1) over running individual country regressions is the ability to include year dummies, which will pick up any global shocks such as the OPEC induced crises or the Great Recession. Indeed, it turns out that these terms are jointly significant.

What are the interpretations of β_i and β_i^D? If in period t GDP grew, then β_i is the effect of a

[3]Countries whose data contain positive outliers are: Angola (1962, 1995), United Arab Emirates (1967, 1969), Burkina Faso (1960), Bahrain (1961), Cameroon (1989, 1992), Iran (1955), Cambodia (1969,1980, 1995), Saint Lucia (1951), Mali (1960), Oman (1967, 1971, 1975), Qatar (1963), Saudi Arabia (1954, 1967), Senegal (1970), Singapore (1967, 1970), Syria (1955) and Trinidad and Tobago (1964).

Countries whose data contain negative outliers are: Cameroon (1986, 1990), Georgia (1995), Iran (1954), Cambodia (1971), Kuwait (1951, 1991), Senegal (1967), Singapore (1966) and Trinidad and Tobago (1963).

one-unit increase in $\Delta lgdp_{it}$ on $\Delta lemis_{it}$, all else constant. Conversely, if in period t GDP declined, then for a one-unit increase in $\Delta lgdp_{it}$, $\Delta lemis_{it}$ rises by $\beta_i + \beta_i^D$, all else constant. Provided that the rate of change of GDP is not big, it is approximately valid to say that a one percentage point (pp) increase in GDP growth rate is associated with β_i pp increase in emissions growth rate in periods of economic growth, and $\beta_i + \beta_i^D$ pp increase in periods of economic decline.

The parameters of equation (1) are estimated by running a fixed effects regression in Stata for the 110 countries and 5668 country-year observations. The null hypothesis of homoskedasticity across countries is rejected (p-value=0.000) in the modified Wald test for groupwise heteroskedasticity. Consequently, I cluster errors at the country level and report robust standard errors. The null hypothesis of no first-order autocorrelation cannot be rejected (p-value=0.357) in the Wooldridge test for autocorrelation in panel data. This is not surprising because both dependent and independent variables are first differenced and I include year fixed-effects.

Two parameters of interest are estimated (i.e. β_i and β_i^D) for each country, so there are 110 parameter pairs. Country level results are reported in the appendix Table A2. Here I focus on the broad patterns summarized in Table 2. For a majority of countries, the estimated parameters are supportive of the hypothesis that the emissions and GDP growth rates are positively correlated in periods of economic growth and decline: in periods of economic growth, β_i is positive in 87 countries out of the total of 110. Conversely, in periods of decline, $\beta_i + \beta_i^D$ is positive in 64 countries.

Against this backdrop, I turn to the main question of this paper, i.e. whether the relationship between emissions and GDP growth rates is stronger during periods of economic decline or growth. Based on (1) it is now possible to provide a more precise definition of the country groups D, S and G informally introduced above. The definition turns on the estimated value and standard error of β_i^D. Specifically, country i is said to be in group D if β_i^D is positive and has a p-value less than 0.05. If the 95% confidence interval for β_i^D includes zero, then country i is in group S. Finally, for group G countries, β_i^D is negative and significant.

Given this definition, there are 37 countries in group D, 33 in group S and 40 in group G. Each group contains countries that can be classified as important according to various criteria. There are advanced economies in all three groups. The US, Canada and Spain are in group D; Japan, the UK and France are in group S; and Switzerland, South Korea and Finland are in group G. Similarly countries with large populations like China, Brazil and India are in groups D, S and G respectively. Finally, it is possible to find large energy importers as well as exporters in each group.

A key conclusion that can be drawn from Table 2 is that there is substantial cross-country heterogeneity in the way changes in emissions and GDP are related in periods of economic growth versus decline. This source of heterogeneity is reflected in the sign of β_i^D, which can be positive, zero or negative. However, this is not the only dimension along which countries differ in Table 2.

A second source of heterogeneity across countries is the strength of the association in periods of growth and decline. Even after excluding some of the extreme β_i and β_i^D which occur in countries with relatively few observations, there remains considerable variation in β_i and β_i^D. As a result, a marginal increase in GDP growth rate in periods of economic expansion may be associated with a more than proportional (e.g. Finland), approximately proportional (e.g. China) or less than proportional (e.g. the USA) increase in the emissions growth rate.

In fact, for 7 countries in the sample, a negative β_i is estimated. These countries are Barbados, Ghana, Malta, Poland, Trinidad and Tobago, Vietnam and Senegal, where a marginal increase in the GDP growth rate in economic expansion is associated with a *decline* in the emissions growth rate. Such a pattern is in principle consistent with an economy experiencing green growth. However, the small size and the diverse composition of this group as well as the fact that these countries exhibit larger than average volatilities in $\Delta lemis_{it}$ suggests idiosyncratic factors are likely to be at play.

Using the estimated values and standard errors of β_i and β_i^D, an analogous observation can be made regarding the magnitude of $\beta_i + \beta_i^D$, i.e. the strength of the association between emissions and GDP growth rates in periods of GDP decline. As mentioned above, $\beta_i + \beta_i^D$ is positive in 64 countries indicating that changes in GDP and emissions growth rates are proportional during periods of economic contraction. Conversely, changes in emissions and GDP are inversely related in 18 countries among which Senegal is the only country for which both β_i and $\beta_i + \beta_i^D$ are negative and statistically significant. In the remaining 28 countries, it is not possible to identify a statistically significant relationship during periods of economic decline. Excluding the most obvious outliers which have only 3 years of economic decline to estimate β_i^D, the value of $\beta_i + \beta_i^D$ is in the range of $[-2.43, 3.51]$.[4] In other words, countries vary significantly in how emissions and GDP are related during periods of economic contraction as well.

I do not attempt to rationalize the cross-country heterogeneity in the sign of β_i^D, or in the magnitudes of the estimated β_i and $\beta_i + \beta_i^D$. The reasons behind these differences are far from obvious. The modest goal of the current paper is to establish the patterns in the data robustly, and point out their potential relevance for climate change policy making. It goes without saying that the net benefits of the introduction of new policies, or the alteration of those already existing, in light of the heterogeneity identified here cannot be evaluated without a better understanding of its drivers in a carefully constructed theoretical model. I leave this much more complex task for future research.

[4] These countries are Tanzania, Israel and Guatemala.

4 Robustness

In order to keep the country coverage of the sample as broad as possible, relatively weak restrictions are imposed on the sample used in the estimation of (1). As explained in section 2, these restrictions exclude from the sample: (i) the country-year observations which are more than 5 standard deviations away from the overall mean of $\Delta lemis_{it}$; and (ii) the countries which have fewer than 3 periods of economic decline.

I briefly discuss the implications of strengthening these restrictions. First, I omit those *countries,* rather than just the offending *country-year observations*, identified by (i). For example, rather than just dropping the observation in 1961 for Bahrain, I drop all observations from Bahrain. Second, I require there to be a minimum of 5 periods of economic contraction. The latter restriction is in part motivated by the fact that the outliers in the distribution of β_i^D tend to be countries that barely meet (ii) with only 3 years of GDP decline.

As a consequence, the sample size drops to 64 countries and 3528 country-year observations. I do not report the detailed results of the estimation with the restricted sample.[5] The restriction implies that 6 of the top 20 emitters in Table 1, are dropped from the estimation sample. Among these, Iran and Saudi Arabia are outliers, and Canada, France, India, and South Korea experience fewer than 5 years of economic decline. Notice that all 3 type G countries in Table 1 are eliminated from the sample. That said, the types of the remaining 14 are unaltered.

More generally, it is important to note that for the 64 countries in both samples the estimated country level parameters are very similar in the restricted and unrestricted samples. However, there are five countries that switch types when the restricted sample is used. This is driven not by large changes in the point estimates of β_i and β_i^D, but by changes in the estimated standard errors of β_i^D.[6]

A final point to highlight is the share of type G countries based on the results from the two samples, which declines from 36% to 23% in the restricted sample. I interpret this as evidence that the identification of type G countries is particularly sensitive to the outliers in the distribution of $\Delta lemis_{it}$ and the inclusion of countries which experience few periods of economic decline. As I show below, how one accounts for outliers is relevant for the results, especially when heterogeneity across countries in β_i and β_i^D is suppressed. What then are the implications of ignoring the heterogeneity apparent in Table 2? The answer to this question is provided in Table 3.

The first column of the table reports the results of the OLS regression where the potential difference in the relation in periods of economic growth and decline as well as across countries is suppressed, i.e. $\beta_i^D = \beta^D = 0$ and $\beta_i = \beta$. However, the regression includes country and year dummies. The value of the unique slope coefficient is precisely estimated to be 0.531.

[5]These results are available upon request.

[6]The countries that switch types are: Denmark (G→S), Estonia (D→S), Iceland (G→S), New Zealand (S→D) and Peru (D→S).

Next, in column (II), I focus on the specification which allows for an asymmetrical relationship in periods of GDP growth and decline, but unlike (1) the specification requires that all countries have the same asymmetrical relationship, i.e. $\beta_i = \beta$ and $\beta_i^D = \beta^D$. It turns out that the estimated β^D is not significant, which means that the slope coefficients are the same in periods of growth and decline. Moreover, the value of β in columns (I) and (II) are statistically the same. Indeed, this value is between the mean and the median of the distribution of β_i obtained from the estimation of (1). In other words, imposing the restriction that all countries have the same slope parameters in periods of growth and decline appears to support the hypothesis that the relationship is symmetrical.

Keeping in mind the heterogeneity in Table 2, the result aligns with one's intuition. β_i^D is approximately symmetrically distributed across the three groups D, S and G. Forcing all countries to have the same slope parameters pits group D countries, which would predispose the estimator to generate a $\beta^D > 0$, against group G countries, which would do the opposite. These two effects balance each other out and provide the illusion that the relationship is symmetrical.

The result that $\beta^D = 0$ in column (II) contradicts the main conclusion of York (2012), which is that the association between the changes in emissions and GDP are stronger during periods of economic expansion, i.e. $\beta^D < 0$. It is important to understand clearly why my results are different from his. To this end I first replicate York's result in column (III), and then show why it is not robust in columns (IV) and (V).

It needs to be emphasized that columns (III)-(V) use the same data as that in section 3. This is not the same as the data in York (2012) which uses emissions and GDP data measured in per capita terms and obtained from the World Bank's World Development Indicators database. As a consequence, the difference in the conclusions of the two studies might be driven by the different data sets. In columns (VI)-(IX), I argue that the difference is not due to the data, but is in fact a direct implication of a few econometric choices in York (2012).

Specifically, column (III) replicates the main conclusion in York (2012). York's uses a generalized least squares technique which assumes that the errors follow an AR(1) process.[7] His regression does not include country and year fixed-effects. York does not provide any information on the variance estimator used, so I assume that the robust standard error option is not specified in his regressions. The parameter estimates I obtain are reported in column (III), and are statistically identical to the results from Model 1 in York (2012). They appear to imply that the relationship between emissions and GDP is weaker in periods of economic decline relative to growth.

Two econometric decisions drive York's result. First, as shown in column (IV), using robust standard errors renders β^D insignificant. Second, the inclusion of country and year dummies reinforces the symmetry result as illustrated in column (V). These dummy variables take account

[7]According to Hoechle (2007) GLS has a tendency to produce optimistic standard errors under the current circumstances.

of some of the unobserved heterogeneity across countries and result in an insignificant coefficient estimate for β^D. It is important to keep in mind, however, that the country and year dummies are only part of the story. What is in fact required is a more flexible specification where in addition to these dummy variables, the slope coefficients are allowed to vary not only across periods of growth and decline, but also across countries.

Finally, columns (VI)-(VIII) are the analogues of columns (III)-(V) but using the data set from the World Bank. The results are very similar except perhaps that the point estimates of the slope parameters are somewhat larger. It turns out that this difference is driven by the fact that York's sample includes the outliers in $\Delta lemis_{it}$. When they are excluded using the same rule described in section 2, the estimated parameters in columns (II), (V), and (IX) are virtually identical. It is reassuring that the results are very similar because the time and country coverage as well as the measurement of the key variables vary across the two data sets.

5 Policy Relevance

The heterogeneity highlighted in this paper is more than just an statistical or academic curiosity. As mentioned in the Introduction, the topic is relevant for policy makers who might want to understand better the future emissions paths associated with projected GDP paths, and how their macroeconomic stabilization policies may affect them. To illustrate, I construct a simple thought experiment.

Suppose there are three countries called d, g and s which are representative members of the groups D, G and S. The goal of the thought experiment is to shed light on the following question. How different are the emissions paths and the level of long run emissions in each country assuming they experience the same GDP path? These paths will be different because the relationship between emissions and GDP are different in periods of economic growth and decline.

In what follows I make some simplifying, albeit strong, assumptions. Specifically:

1. Countries d, g and s are parametrized by the coefficient estimates obtained from estimating (1) for each group D, G and S separately. In other words, I allow for cross group heterogeneity but suppress cross-country heterogeneity. In estimation, I use the restricted sample discussed in the previous section to minimize potential biases that may be introduced by outliers.

2. There is no uncertainty about the profile of GDP, which grows for 4 periods at $g_y = 0.03$ per period in periods of expansion. This is followed by a period of decline where GDP decreases by $g_y^D = -0.05$. The deterministic cycle repeats itself 3 times resulting in 22% growth in GDP over the 15-period horizon. I refer to the level of emissions in period 15 as long run emissions.

3. I assume variations in GDP cause variations in emissions and all factors other than GDP that have a bearing on emissions dynamics are constant.

The results from the regressions described in the first assumption are reported in Table 4. Notice that $\beta_d < \beta_s < \beta_g$ while at the same time $\beta_d + \beta_d^D > \beta_s + \beta_s^D > \beta_g + \beta_g^D$. In other words, a 1 pp increase in the GDP growth rate during economic expansions is associated with progressively greater increases in emissions growth rate in countries d, s and g during periods of economic growth. The opposite is true during periods of decline. As a consequence, the same GDP profile can be consistent with different emissions profiles and long run emissions.

In order to show this, I use the group specific β and β^D to simulate the emissions paths associated with the GDP dynamics given in assumption 2. For each country the initial period emissions are set to 100. The results of this simple simulation exercise are plotted in the left panel of Figure 1. For the same GDP dynamics and starting point, long run emissions in country d decline by 5%, whereas country s and g emissions increase by 12% and 26% respectively. Such differences are large enough to have implications for international climate-change negotiations. Moreover, given that there are several large emitters in group D, long run global projections based on parameter estimates from analyses which suppress heterogeneity would be overly pessimistic.

A final point relevant for policy makers relates to macroeconomic stabilization policies. Suppose the government can implement a policy which can reduce the extent of the GDP decline at the cost of a lower growth rate during periods of expansion. For example, the pair $g_y = 0.02$ and $g_y^D = -0.012$ ensures that the amplitude is lower while the average growth rate over the long run is the same. Assuming that the stabilization policy does not affect the relationship between emissions and GDP, the implications of the policy for long run emissions are significant. They are illustrated in the right panel of Figure 1, which is drawn to the same scale to facilitate comparison.

Note, first of all, the compression in emissions paths and the subsequent long run levels relative to the case with no stabilization policy. This is to be expected as GDP cycles feature a smaller amplitude with stabilization policy. A more subtle result emerges from the comparison of each country's emissions before and after the stabilization policy. For instance, country d emissions no longer decline but in fact increase by 4% over the horizon considered. As a consequence of symmetry, country s emissions are approximately the same, Finally, the emissions increase in country g is attenuated as emissions rise by 17% in a more stable macroeconomic environment. Put differently, an effective stabilization policy makes emissions targets harder to achieve in country d and easier in country g because of the path dependency of emissions when the relationship is asymmetrical.

It is essential to underline that the empirical evidence provided in this paper can be consistent with a number of underlying economic mechanisms. In the absence of a theoretical model which rationalizes these observations, one must not read too much into the correlations identified above and, in particular, refrain from making specific policy recommendations. Perhaps, the most important policy message that emerges is that the emissions projections made with models which do not incorporate occasional periods of GDP decline combined with an asymmetrical response of emissions to changes in GDP should be treated with much caution.

6 Conclusion

The paper demonstrates that for a large majority of countries in the world the relationship between changes in emissions and GDP is different in periods of economic growth relative to decline. Moreover, there is significant quantitative heterogeneity in the strength of the relationship between emissions and GDP both during periods of growth and decline. These results are novel and stand in contrast to York (2012).

I demonstrate that the heterogeneity might be important for policy. In particular, accounting for heterogeneity is crucial for models used in making long run emissions projections, which in turn produce critical inputs into the international climate change negotiation process. I argue that heterogeneity is also key for the co-benefits and unintended costs of macroeconomic stabilization policies. While the current paper documents the heterogeneity in the emissions-GDP relationship, it is entirely silent on the question of the drivers of this heterogeneity. However, the results presented in this paper suggest that further research on these drivers is much needed.

References

BBC. (2010). *2009 carbon emissions fall smaller than expected.* Link to webpage (accessed March 2013)

Boden TA, Marland G, Andres RJ. (2012). *Global, Regional, and National Fossil-Fuel CO2 Emissions.* Carbon Dioxide Information Analysis Center, Oak Ridge National Laboratory, U.S. Department of Energy, Oak Ridge, Tenn., U.S.A. Link to webpage (accessed March 2013)

Conference Board (2013). *Total Economy Database.* Link to webpage (accessed March 2013)

Doda B. (2012). *Evidence on CO2 emissions and business cycles.* Working paper 78, Grantham Research Institute on Climate Change and the Environment, London, UK.

Financial Times. (2009). *Recession results in steep fall in emissions. Link to webpage* (accessed March 2013)

Fischer C, Springborn M. (2011). *Emissions targets and the real business cycle: Intensity targets versus caps or taxes.* Journal of Environmental Economics and Management vol. 62. p352–366.

Heutel G. (2012). *How Should Environmental Policy Respond to Business Cycles? Optimal Policy under Persistent Productivity Shocks.* Review of Economic Dynamics. vol. 15(2). p244-264.

Hoechle D. (2007). *Robust standard errors for panel regressions with cross-sectional dependence.* The Stata Journal. vol. 7(3). p281-312.

Huffington Post. (2012). *Greenhouse Gas Emissions Rise With GDP But Slower To Fall During Recession, Study Finds. Link to webpage* (accessed March 2013)

Jotzo F, Burke PJ, Wood PJ, Macintosh A, Stern, DI. (2012). *Decomposing the 2010 global carbon dioxide emissions rebound.* Nature Climate Change. vol. 2(4). p213-214.

Peters GP, Marland G, Le Quere C, Boden T, Canadell JG, Raupach MR. (2012). *Rapid growth in CO2 emissions after the 2008-2009 global financial crisis.* Nature Climate Change. vol. 2(1). p2-4.

Wall Street Journal. (2010). *The Carbon Recession CO2 emissions plunge, along with the economy. Washington rejoices. Link to webpage* (accessed March 2013)

York R. (2012). *Asymmetric effects of economic growth and decline on CO2 emissions.* Nature Climate Change. vol. 2(11). p762-764.

Table 1: Grouping top 20 emitters

	Group D	**Group S**	**Group G**
	China (5/61) US (8/61) Russia (6/19) Iran (10/60) Canada (4/61) Indonesia (6/61) Mexico (6/61) Poland (10/61) Spain (5/61)	Japan (6/61) Germany (6/61) South Africa (8/61) UK (9/61) Italy (5/61) Brazil (6/61) France (4/61) Turkey (7/61)	India (4/61) Korea (3/61) Saudi Arabia (5/58)
Group's share of world emissions	56.6%	13.9%	9.6%

Notes:

1) Group D countries are characterized by a stronger association between emissions growth and GDP growth in periods of economic decline relative to expansion. The opposite is true for group G countries. For group S countries, the association is statistically the same in periods of decline and expansion, where statistical significance evaluated based on the p-value of the associate test being less than 0.05.

2) For each country, the figures in parenthesis indicate the number of periods in which GDP declines and the number of total data points.

3) The estimation results for Iran, Canada, France, India, Korea and Saudi Arabia are less reliable because of data quality issues, or relatively few periods in which GDP declines. See the discussion in Section 3.

4) Country rankings are based on 2009 emissions data. Turkey, which ranks 21st in the top emitters list, replaces Australia because the latter has only two periods of economic decline.

Table 2: Heterogeneity in β_i and β_i^D

Economic Decline

Economic Growth		Group D $\beta_i^D > 0$					Group S $\beta_i^D \approx 0$					Group G $\beta_i^D < 0$			
		$N = 22$					$N = 28$					$N = 37$			
$\beta_i > 0$		Mean	Std. Dev.	Min	Max		Mean	Std. Dev.	Min	Max		Mean	Std. Dev.	Min	Max
	β	0.490	0.192	0.267	0.948	β	0.631	0.317	0.162	1.723	β	1.121	0.812	0.099	3.517
	β^D	0.977	0.701	0.283	3.111	β^D	0.103	0.432	-0.942	1.373	β^D	-2.089	3.893	-23.471	-0.173
		$N = 9$					$N = 5$					$N = 2$			
$\beta_i \approx 0$		Mean	Std. Dev.	Min	Max		Mean	Std. Dev.	Min	Max		Mean	Std. Dev.	Min	Max
	β	0.040	0.089	-0.088	0.172	β	0.013	0.163	-0.124	0.280	β	0.026	0.020	0.012	0.040
	β^D	1.421	1.355	0.317	4.388	β^D	0.184	0.271	-0.216	0.477	β^D	-0.817	0.742	-1.342	-0.292
		$N = 6$					$N = 0$					$N = 1$			
$\beta_i < 0$		Mean	Std. Dev.	Min	Max		Mean	Std. Dev.	Min	Max		Mean	Std. Dev.	Min	Max
	β	-0.568	0.277	-1.049	-0.265	β	-	-	-	-	β	-0.999	0	-0.999	-0.999
	β^D	2.044	0.602	1.350	2.763	β^D	-	-	-	-	β^D	-0.903	0	-0.903	-0.903

Notes:

1) See the notes to Table 1 for the definitions of groups D, S and G.

2) Each cell in the table reports summary statistics for alternative sign combinations of $\{\beta, \beta^D\}$. For example, the statistics in the top left cell indicate that there are 22 countries with $\beta > 0$ and $\beta^D > 0$. Robust standard errors from the estimation of (1) are used to evaluate significance at 0.05 level.

3) Individual country results are provided in the appendix Table A2.

Table 3: Implications of suppressing heterogeneity

	I	**II**	**III**	**IV**	**V**	**VI**	**VII**	**VIII**	**IX**
β	0.531	0.506	0.702	0.702	0.522	0.833	0.833	0.781	0.583
$p-value$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
β^D	na	-0.063	-0.203	-0.203	-0.020	-0.297	-0.297	-0.293	-0.076
$p-value$		0.703	0.012	0.191	0.894	0.003	0.096	0.124	0.584
Forced symmetry?	Y	N	N	N	N	N	N	N	N
Country and year F.E.?	Y	Y	N	N	Y	N	N	Y	Y
Estimation technique?	OLS	OLS	GLS	GLS	GLS	GLS	GLS	GLS	GLS
Robust standard errors?	Y	Y	N	Y	Y	N	Y	Y	Y
Sample?	S3	S3	S3	S3	S3	WDI	WDI	WDI	WDIx
# of countries/observations	110/5668			110/5668			160/5894		160/5865

Notes:

1) S3 refers to the sample used in the estimation of (1) in section 3.

2) WDI refers to the sample drawn from the World Bank's WDI database as in York (2012). (i.e. only countries with populations larger than 500,000 in 2008 are included.)

3) WDIx refers to WDI with the additional restriction that outliers as defined in section 2 are excluded.

Table 4: Parameters for the thought experiment

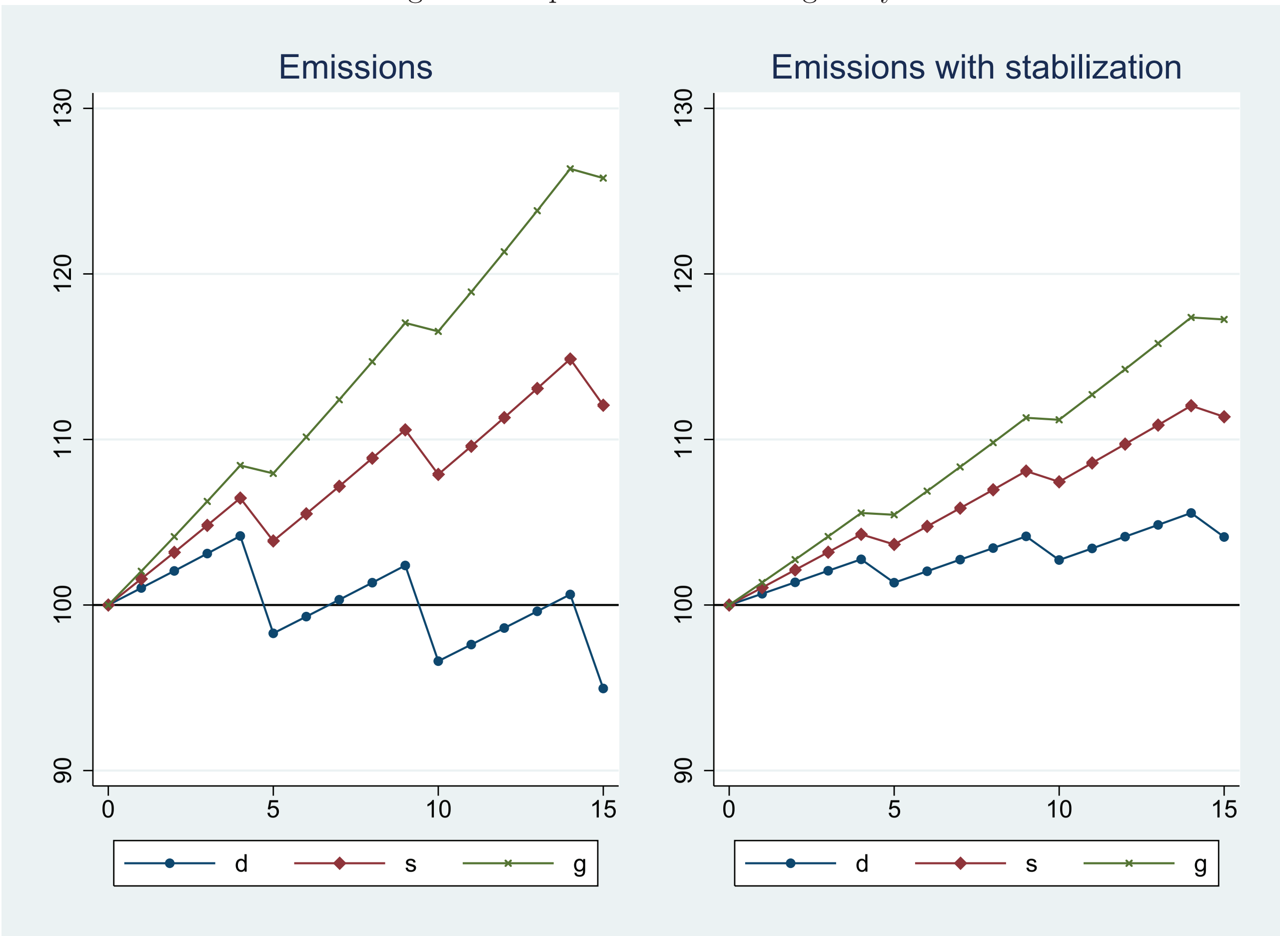
	Group D	Group S	Group G
β	0.342	0.526	0.681
$p-value$	0.025	0.000	0.002
β^D	0.786	-0.039	-0.593
$p-value$	0.001	0.811	0.015
# of countries	25	24	15
# of observations	1355	1346	827
Country and year F.E.?		YES	
Estimation technique?		OLS	
Robust standard errors?		YES	

Notes:

1) See the notes to Table 1 for the definitions of groups D, S and G.

2) Group specific regressions are run using the restricted sample described in Section 4. The restricted sample excludes countries whose data contains extreme outliers for $\Delta lemis_{it}$ and those countries which has fewer than 5 periods of economic decline.

Figure 1: Implications of heterogeneity



Appendix:

Table A1: Description of the data set

Country	**Data starts**	**Data points**	**Periods of decline**	**Outlier?**
Angola	1951	59	13	*
Albania	1951	59	3	
United Arab Emirates	1960	50	9	*
Argentina	1951	61	18	
Armenia	1993	17	2	
Australia	1951	61	2	
Austria	1951	61	4	
Azerbaijan	1993	19	3	
Belgium	1951	59	7	
Burkina Faso	1959	51	9	*
Bangladesh	1973	39	1	
Bulgaria	1951	61	15	
Bahrain	1951	59	4	*
Bosnia and Herzegovina	1993	17	2	
Belarus	1993	19	3	
Bolivia	1951	59	10	
Brazil	1951	61	6	
Barbados	1951	59	7	
Canada	1951	61	4	
Switzerland	1951	61	8	
Chile	1951	61	9	
China	1951	61	5	
Cote D Ivoire	1959	51	12	
Republic of Cameroon	1951	59	8	*
DR Congo	1951	59	22	
Colombia	1951	61	1	
Costa Rica	1951	59	4	
Cyprus	1951	59	7	
Czech Republic	1993	19	3	
Germany	1951	61	6	

Table A1 (cont.): Description of the data set

Country	Data starts	Data points	Periods of decline	Outlier?
Denmark	1951	61	7	
Dominican Republic	1951	59	6	
Algeria	1951	61	11	
Ecuador	1951	61	3	
Egypt	1951	61	1	
Spain	1951	61	5	
Estonia	1993	17	5	
Ethiopia	1951	59	9	
Finland	1951	61	5	
France	1951	61	4	
United Kingdom	1951	61	9	
Georgia	1993	17	3	*
Ghana	1951	59	10	
Greece	1951	61	7	
Guatemala	1951	59	3	
Hong Kong	1951	61	3	
Croatia	1993	17	3	
Hungary	1951	61	10	
Indonesia	1951	61	6	
India	1951	61	4	
Ireland	1951	61	8	
Iran	1952	60	10	*
Iraq	1951	59	21	
Iceland	1951	59	10	
Israel	1951	61	3	
Italy	1951	61	5	
Jamaica	1951	59	12	
Jordan	1951	59	6	
Japan	1951	61	6	
Kazakhstan	1993	19	4	

Table A1 (cont.): Description of the data set

Country	Data starts	Data points	Periods of decline	Outlier?
Kenya	1951	59	6	
Kyrgyzstan	1993	17	5	
Cambodia	1956	54	8	*
Republic Of Korea	1951	61	3	
Kuwait	1951	58	13	*
Saint Lucia	1951	59	3	*
Sri Lanka	1951	59	3	
Lithuania	1993	19	4	
Luxembourg	1951	59	5	
Latvia	1993	17	4	
Morocco	1951	59	7	
Republic Of Moldova	1993	17	7	
Madagascar	1951	59	13	
Mexico	1951	61	6	
Macedonia	1993	17	5	
Mali	1960	50	10	*
Malta	1951	59	6	
Myanmar	1951	59	7	
Mozambique	1951	59	9	
Malawi	1965	45	5	
Malaysia	1971	41	3	
Niger	1959	51	15	
Nigeria	1951	59	14	
Netherlands	1951	61	4	
Norway	1951	61	2	
New Zealand	1951	61	10	
Oman	1965	45	3	*
Pakistan	1973	39	0	
Peru	1951	61	9	
Philippines	1951	61	4	

Table A1 (cont.): Description of the data set

Country	Data starts	Data points	Periods of decline	Outlier?
Poland	1951	61	10	
Portugal	1951	61	8	
Qatar	1951	61	10	*
Romania	1951	61	14	
Russian Federation	1993	19	6	
Saudi Arabia	1954	58	5	*
Sudan	1951	59	14	
Senegal	1959	49	10	*
Singapore	1958	54	6	*
Slovakia	1993	19	1	
Slovenia	1993	17	1	
Sweden	1951	61	7	
Syria	1951	59	15	*
Thailand	1951	61	4	
Tajikistan	1993	17	4	
Turkmenistan	1993	19	3	
Trinidad and Tobago	1951	61	12	*
Tunisia	1951	59	8	
Turkey	1951	61	7	
Taiwan	1951	61	2	
Tanzania	1971	39	3	
Uganda	1951	59	9	
Ukraine	1993	19	8	
Uruguay	1951	59	13	
United States of America	1951	61	8	
Uzbekistan	1993	19	3	
Venezuela	1951	61	13	
Viet Nam	1971	41	3	
Yemen	1992	18	0	
South Africa	1951	61	8	
Zambia	1965	45	15	
Zimbabwe	1965	45	14	

Table A2: Country level estimation results

Country	β	$p-value$	β^D	$p-value$	$Type$
Angola	0.41	0.00	-0.36	0.00	G
Albania	2.37	0.00	-0.51	0.00	G
United Arab Emirates	0.04	0.25	0.45	0.00	D
Argentina	0.16	0.10	0.32	0.03	D
Armenia			*excluded*		
Australia			*excluded*		
Austria	0.60	0.00	0.54	0.19	S
Azerbaijan	0.70	0.00	-0.17	0.00	G
Belgium	0.78	0.00	-0.31	0.57	S
Burkina Faso	0.16	0.00	0.22	0.44	S
Bangladesh			*excluded*		
Bulgaria	0.34	0.00	0.94	0.00	D
Bahrain	0.85	0.00	-1.82	0.00	G
Bosnia and Herzegovina			*excluded*		
Belarus	0.82	0.00	-0.37	0.01	G
Bolivia	0.60	0.00	-0.28	0.20	S
Brazil	0.64	0.00	0.08	0.77	S
Barbados	-0.63	0.00	2.42	0.00	D
Canada	-0.04	0.75	1.15	0.02	D
Switzerland	1.19	0.00	-0.98	0.00	G
Chile	0.33	0.00	0.59	0.00	D
China	0.95	0.00	1.06	0.00	D
Cote D Ivoire	0.36	0.00	2.08	0.00	D
Republic of Cameroon	2.87	0.00	-2.53	0.00	G
DR Congo	0.52	0.00	0.49	0.00	D
Colombia			*excluded*		
Costa Rica	0.56	0.00	-0.90	0.00	G
Cyprus	0.59	0.00	-0.08	0.32	S
Czech Republic	0.72	0.00	-0.49	0.15	S
Germany	0.24	0.01	0.34	0.26	S
Denmark	0.50	0.00	-0.52	0.05	G
Dominican Republic	0.80	0.00	0.60	0.00	D

Table A2 (cont.): Country level estimation results

Country	β	$p-value$	β^D	$p-value$	$Type$
Algeria	0.44	0.00	-0.24	0.00	G
Ecuador	0.34	0.00	0.59	0.02	D
Egypt			*excluded*		
Spain	0.40	0.00	3.11	0.00	D
Estonia	0.59	0.00	0.33	0.04	D
Ethiopia	0.52	0.00	-0.61	0.00	G
Finland	1.23	0.00	-1.33	0.00	G
France	0.78	0.00	-0.94	0.06	S
United Kingdom	0.36	0.01	0.29	0.50	S
Georgia	2.79	0.00	-1.66	0.00	G
Ghana	-0.59	0.00	1.35	0.00	D
Greece	0.39	0.00	0.52	0.01	D
Guatemala	-0.09	0.32	4.39	0.00	D
Hong Kong	0.39	0.00	-2.58	0.00	G
Croatia	0.75	0.00	-0.43	0.15	S
Hungary	0.59	0.00	0.16	0.28	S
Indonesia	0.47	0.00	1.46	0.00	D
India	0.39	0.00	-0.99	0.01	G
Ireland	0.62	0.00	-0.15	0.66	S
Iran	0.63	0.00	0.28	0.00	D
Iraq	0.58	0.00	-0.48	0.00	G
Iceland	0.79	0.00	-0.58	0.01	G
Israel	0.72	0.00	-8.10	0.00	G
Italy	1.01	0.00	0.30	0.32	S
Jamaica	1.72	0.00	0.01	0.95	S
Jordan	0.39	0.00	0.14	0.34	S
Japan	0.83	0.00	-0.08	0.80	S
Kazakhstan	1.76	0.00	-1.36	0.00	G
Kenya	1.33	0.00	-2.42	0.00	G
Kyrgyzstan	0.45	0.00	1.14	0.00	D
Cambodia	0.60	0.00	1.87	0.00	D
Republic of Korea	0.65	0.00	-1.13	0.00	G

Table A2 (cont.): Country level estimation results

Country	β	$p-value$	β^D	$p-value$	$Type$
Kuwait	0.62	0.00	-0.74	0.00	G
Saint Lucia	0.04	0.37	-1.34	0.00	G
Sri Lanka	0.78	0.00	1.37	0.25	S
Lithuania	0.72	0.00	0.02	0.87	S
Luxembourg	1.09	0.00	-1.61	0.00	G
Latvia	1.45	0.00	-1.50	0.00	G
Morocco	0.37	0.00	-0.86	0.00	G
Republic Of Moldova	3.52	0.00	-3.59	0.00	G
Madagascar	0.05	0.62	2.55	0.00	D
Mexico	0.33	0.00	0.69	0.00	D
Macedonia	0.28	0.14	0.09	0.74	S
Mali	0.36	0.00	0.10	0.46	S
Malta	-0.54	0.00	1.88	0.00	D
Myanmar	0.39	0.00	1.04	0.00	D
Mozambique	0.91	0.00	0.33	0.01	D
Malawi	0.05	0.31	0.19	0.19	S
Malaysia	0.46	0.00	1.23	0.00	D
Niger	0.01	0.86	-0.29	0.00	G
Nigeria	2.04	0.00	-2.45	0.00	G
Netherlands	0.44	0.00	0.59	0.19	S
Norway			*excluded*		
New Zealand	0.27	0.00	0.41	0.07	S
Oman	0.05	0.05	0.65	0.00	D
Pakistan			*excluded*		
Peru	0.60	0.00	0.30	0.01	D
Philippines	-0.05	0.63	2.08	0.00	D
Poland	-0.27	0.02	1.37	0.00	D
Portugal	0.48	0.00	-0.32	0.41	S
Qatar	0.75	0.00	-1.04	0.00	G
Romania	0.27	0.01	1.52	0.00	D
Russian Federation	0.17	0.18	0.68	0.00	D
Saudi Arabia	0.96	0.00	-1.87	0.00	G

Table A2 (cont.): Country level estimation results

Country	β	$p-value$	β^D	$p-value$	$Type$
Sudan	0.10	0.00	-1.03	0.00	G
Senegal	-1.00	0.00	-0.90	0.00	G
Singapore	1.69	0.00	-4.12	0.00	G
Slovakia			*excluded*		
Slovenia			*excluded*		
Sweden	0.47	0.00	0.43	0.18	S
Syria	0.18	0.00	-0.28	0.02	G
Thailand	0.89	0.00	0.27	0.08	S
Tajikistan	1.08	0.00	-0.06	0.63	S
Turkmenistan	1.23	0.00	-2.38	0.00	G
Trinidad and Tobago	-0.33	0.00	2.48	0.00	D
Tunisia	-0.06	0.41	0.38	0.18	S
Turkey	0.57	0.00	0.21	0.40	S
Taiwan			*excluded*		
Tanzania	2.40	0.00	-23.47	0.00	G
Uganda	1.22	0.00	-0.81	0.00	G
Ukraine	0.31	0.00	0.37	0.00	D
Uruguay	1.00	0.00	-0.68	0.00	G
United States of America	0.36	0.01	0.98	0.03	D
Uzbekistan	0.22	0.02	0.55	0.15	S
Venezuela	-0.08	0.16	-0.22	0.14	S
Viet Nam	-1.05	0.00	2.76	0.00	D
Yemen			*excluded*		
South Africa	-0.12	0.23	0.48	0.46	S
Zambia	0.99	0.00	-1.20	0.00	G
Zimbabwe	0.05	0.33	0.52	0.00	D