An Estimate of the Age Distribution's Effect on Carbon Dioxide Emissions*

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We estimate the age distribution's impact on carbon dioxide emissions from 1990 to 2006 by exploiting demographic variation in a panel of 46 countries. To eliminate potential bias from endogeneity or omitted variables, we instrument for the age distribution in a country's current population with lagged birth rates, and the regressions control for total population, total output, and country and year fixed effects. Carbon dioxide emissions increase with the share of the population aged 35 to 49, and this result is statistically significant and quantitatively large.

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1 Introduction

We exploit temporal and geographic demographic variation to estimate the relationship between a population's age distribution and carbon dioxide (CO_2) emissions in a panel of 46 countries from 1990 to 2006. To reduce potential omitted variable bias, we instrument for the age distribution with lagged birth rates and control for total population and total gross domestic product (GDP). A higher share of prime working age (35-49) individuals within a country leads to higher CO_2 emissions, while younger and older populations have lower CO_2 emissions according to our results.

Emissions of CO_2 account for about half of the radiative forcing from anthropogenic sources that are considered the primary contributors to global warming. The 2007 Intergovernmental Panel on Climate Change predicts increases in average surface temperatures in the range of 1.1 to 6.4 degrees Centigrade (2 to 11.5 degrees Fahrenheit) by the end of the century. Climate change has created the threat of substantial environmental damage, with the possibility of catastrophic consequences for many throughout the world. As a result, both academics and policy-makers are interested in CO_2 emissions.

The literature aimed at explaining CO_2 emissions usually focuses on the size and affluence of the population. This approach can be traced back to the seminal work by Ehrlich and Holdren (1971), the biologist and physicist who argued that population *size* has a disproportionate impact on the environment. The impact is generally assumed to depend upon affluence and technology, leading to the well-known IPAT identity, $I = P \times A \times T$, where I is environmental impact, P is population size, A is affluence (GDP per capita), and T is a technology index. More recent literature has focused on models of the technology index and how the index changes over time (e.g. due to improvements in abatement technology). The widely cited Intergovernmental Panel on Climate Change studies use several variations of the IPAT model to produce regional emissions forecasts, which are then aggregated to the global level. Structural studies by economists (e.g. Nordhaus 2009) have also attempted to forecast global CO_2 emissions using estimates of GDP from production functions and world population size. Although these studies have frequently used geographic density of the population as well as its size as explanatory variables, and have allowed for nonlinearity in size, most have ignored the age distribution within the population.[1]

A few papers have begun to address this potential oversight by explicitly including the age distribution in studies of CO_2 emissions. Dalton et al. (2008) build a structural overlapping generations model to forecast US CO_2 emissions.[2] In their model simulations, population aging has a big effect on future emissions. Our empirical findings support Dalton et al. (2008), but our approach is most closely related to Cole and Neumayer (2004).[3] Cole and Neumayer (2004) also use a cross-country panel to estimate the effect of demographic change on CO_2 emissions in an IPAT type regression model. While Cole and Neumayer (2004) include age group shares as controls, the groups (younger than 15, 15-64, and 65+) are too wide to capture the effect we posit, and they do not instrument for the age distribution as we do. Cole and Neumayer (2004) mainly focus on changes in total population; whereas, we are interested in the age distribution effect for a given population size.

Our ordinary least square (OLS) estimates indicate that a country's level of CO_2 emissions depends on its age distribution. In addition to population size, the regressions include total GDP and a full set of time and country dummies as controls. We use the fraction of the population aged 35-49, or working share, as the main explanatory variable. Changes in the working share across time, not common to all countries, and independent of GDP and total

[1] Auffhammer and Steinhauser (2012) offer an excellent survey of the CO_2 emissions literature and examine thousands of models, none of which include the age distribution as an explanatory variable.

[2] Several papers develop structural models to study the environment more generally. John and Pecchenio (1994) examine the welfare implications of environmental protection in an overlapping generations framework. Gerlagh and van der Zwaan (2000) explore several potential policies for lowering pollution. Kelly and Kolstad (2001) build a simple representative agent model to study population growth and the environment.

[3] Also see Schmalensee et al. (1998) and Liddle and Lung (2010).

population provide the variation used to estimate the age distribution's effect.

Unfortunately, the OLS estimates may suffer from omitted variable bias. Country and year specific factors affecting CO_2 emissions, but not included in the regression equations, could alter the age distribution. For example, an economic boom might induce both an increase in the consumption (or production) of goods related to CO_2 emissions (such as transportation or the construction of new buildings) and in-migration of younger, more mobile, age groups. Similarly, CO_2 emissions may be correlated with current birth rates or with old age mortality. These changes to the age distribution would mechanically reduce the working share and bias the OLS estimates downward. Endogeneity is possible, too. For example, location choices could differ by age group as a function of environmental quality. Classical measurement error could also shrink the OLS estimates.

To address the potential bias, we instrument for the current working share with the birth rates from 10, 20, 30, and 40 years ago. The working share depends on past birth rates. Future CO_2 levels probably did not enter into past fertility decisions, and we assume that other determinants of emissions (such as current business cycles and the age distribution itself) did not enter past fertility decisions, either. Thus, identification of the age distribution's effect on CO_2 emissions in the two-stage least squares (2SLS) regressions relies on differential changes in birth rates across the panel of countries.

In a back of the envelope calculation the point estimate from the baseline 2SLS regression implies that demographic change accounts for about 60% of the recent CO_2 emissions increase. The OLS estimate and some of the robustness checks are smaller than the baseline (though still big), and the estimates (though statistically significant) have large standard errors. Thus, instead of a single number we prefer the simple conclusion that the age distribution has a quantitatively large effect on CO_2 emissions.

That the age distribution of the population *per se* has a nontrivial effect on the level of CO_2 emissions should not be viewed as a surprise. Production tends to increase with the fraction of the population employed, so linking emissions to the working share seems a natural conjecture. The surprise is, perhaps, that little attention has been paid to the age distribution's potential impact on CO_2 emissions. After all, economists and policy-makers have long been concerned about the effects of demographic change on the social safety net. Moreover, life-cycle patterns in the level of consumption reinforce the connection between the age structure and CO_2 emissions. Lifetime consumption follows a hump shape, rising as people age, reaching a maximum during the prime working years, and tapering off late in life. Thus, we should expect greater CO_2 emissions for a population with a higher fraction of people in their prime working years due to higher production and consumption. Note, though, our regressions partially control for this direct effect by including GDP as a covariate.

We think life-cycle patterns in the types of goods consumed are responsible for our findings; people aged 35-49 consume goods that generate relatively greater CO_2 emissions than other age groups. For example, Zagheni (2011) constructs estimates from micro data showing that prime working age adults in the US consume relatively more CO_2-intensive goods. Fernandez-Villaverde and Krueger (2007) also provide evidence on how the mix of goods consumed changes over the life cycle. Admittedly, some of the increased consumption of CO_2-intensive goods in the peak working years may be imported. However, Aguiar and Hurst (2010) find that much of the increased consumption involves work-related non-durables such as transportation, which is the second-leading source of CO_2 emissions. An automobile driven on local roads generates domestic CO_2 emissions, wherever it was produced.[4] The life-cycle consumption pattern represents one compelling explanation for our results; however, the regressions cannot fully rule out the production side, a possibility we discuss further

[4]See Glaeser and Kahn (2010); they estimate CO_2 emissions from automobile use and other sources at the household level in 66 major metropolitan areas in the United States.

below.[5] Either way, the age distribution's effect on CO_2 emissions is large.

From a global reduction perspective, the age distribution effect may not, in itself, suggest a particular policy (short of potentially terrifying prescriptions) because people age one year each year. However, the relationship could matter a great deal for individual countries or blocks of countries entering environmental pacts and for their optimal strategy in international climate negotiations. Also, further research aimed at uncovering the specific channel(s) through which the age distribution affects emissions might generate insights relevant for policies aimed at global CO_2 reduction. Thus, while we do not focus on forecasting future CO_2 emissions or constructing policy, our findings should be of interest to those that do. Attempts at both domestic regulation and international negotiation, such as the Kyoto protocol, have taken the projected growth of GDP and total population size into account explicitly, but overlooked changes in the age distribution. If our results continue to hold in the near future, then the aging of the baby boomers will reduce CO_2 emissions in the United States and other developed countries. Conversely, demographic changes might increase emissions in developing countries. Calculations based on United Nation's age distribution projections and our regression results indicate that accounting for the changing age distribution would increase forecasts of CO_2 emissions by more than 15% in developing countries over the next ten to twenty years.

The next section summarizes the within- and cross-country variation in the data. Section 3 presents the results and robustness checks, along with additional discussion of the findings. Section 4 concludes.

[5] Populations with different age distributions could employ different technologies, generating different amounts of CO_2, to produce the same goods or goods of the same value.

2 Data and Identification Strategy

We use a balanced panel with 782 total annual observations on 46 countries over 17 years (1990-2006). The set of countries displays economic and geographic diversity. Data on CO_2 emissions and GDP comes from the World Bank's World Development Indicators. Age distribution information comes from the United Nations World Population Prospects. The Appendix provides additional details on the data sources.

Figure 1 plots average logged total CO_2 emissions as a solid line (left axis) and the average working share, number of people aged 35-49 divided by the total population, as a dotted line (right axis) against time for the sample of 46 countries. Both clearly trend up. While provocative, the time series correlation could be spurious. Thus, we leverage the variation across countries to estimate the age distribution's effect on CO_2 emissions.

Figure 2 plots total CO_2 emissions and the working share over time for each country. The different patterns within countries provide the variation necessary to estimate the working share's effect on CO_2 emissions. Many places (e.g. Chile, Ireland, New Zealand, Sri Lanka, Spain, and Thailand) follow the global trend of increasing working share and emissions, while others (e.g. Denmark, Hungary, and Sweden) have a downward trend. The scale of CO_2 emissions varies, highlighting the need for country fixed effects in the regressions. For Romania and the United Kingdom the working share and CO_2 go in opposite directions. Overall, though, emissions appear to move with the working share in most countries.

The working share variable is probably stationary by construction, and several countries (Australia, Canada, France, Poland, the US, etc.) have hump shaped working shares in Figure 2. The robustness checks address the possibility of non-stationarity in the other variables. We also checked whether the working share and total CO_2 emissions are co-integrated using the four panel tests presented in Persyn and Westerlund (2008). The null of no co-integration could not be rejected for any of the tests. Thus, while non-stationary variables and co-integration can make estimates of the relationship between emissions and GDP unreliable (see Stern (2004) and the references within for more on this), these do not appear to be a problem for us. Instead, we worry more about omitted variables and endogeneity.

Omitted variables or endogeneity might bias OLS estimates, so we instrument for the current working share with birth rates from 10, 20, 30, and 40 years ago. The United Nations 1997 Demographic Yearbook reports past birth rates for many countries, but the availability of reliable birth rate data restricts the sample.[6] Access to birth control, government family-planning policies, cultural norms, wars, disease, and even weather patterns have been known to cause variation in birth rates, and ample demographic variation exists to estimate the working share's impact on CO_2 emissions.

We assume the variation in fertility was caused by factors unrelated to current CO_2 emissions. As with any instrument, an omitted variable could affect both lagged birth rates and current CO_2 emissions, violating the exclusion restriction assumption. However, given the temporal structure of the data, candidate variables are difficult to imagine. The four instruments span 30 years and have different effects from each other on the age distribution and, in a reduced form regression, on CO_2 emissions (see Table 3). Thus, we believe birth rates are a valid instrument. Also, instrumenting for the age distribution with lagged birth rates has been done before in other contexts. Shimer (2001) measures the age distribution's effect on the unemployment rate; Feyrer (2007) relates the age distribution to productivity; and Lugauer (2012) considers whether the age distribution affects the magnitude of business cycles. We turn now to the regression analysis.

[6] For example, the baseline panel does not include Germany, Brazil, Russia, India, or China because of data limitations. These countries are included in Figure 2 and used in some of the robustness checks below.

3 Results

Equation 1 captures the relationship of interest:

$$CO2_{i,t} = \alpha_i + \beta_t + \gamma ws_{i,t} + controls_{i,t}\delta + \varepsilon_{i,t}. \tag{1}$$

Variable $CO2$ represents logged total kilotons of CO_2 emissions in country i during year t. The α represents country fixed effects to control for time-invariant differences in $CO2$ levels across countries, possibly due to environmental policy, source of power, industry specialization, automobile use, or geography.[7] The β represents year effects to control for shocks and global time trends common to all countries. The working share variable ws equals the percentage of the population aged 35-49 in country i during year t.[8] The working share is our measure of the age distribution, and primarily we are interested in the age distribution's effect on $CO2$. Identification of the working share effect, γ, comes from changes in the working share over time not common across countries. The control variables include total real GDP, GDP^2, and total population all in logs.[9] Thus, the estimated working share effect is net of the level of output and total population.[10] For reference, Table 1 reports the mean of each variable across the 46 countries. The term ε_{it} captures other sources of variation in CO_2 emissions.

[7] The first four also could vary over time. We discuss these possibilities below.

[8] Equation 1 implicitly assumes age groups outside 35-49 have a homogeneous effect. A robustness check includes other age groups. The results do not change appreciably.

[9] We use the log of total CO_2 emissions rather than per capita emissions because the regressions explicilty include logged total population as a control. Using per capita emissions by subtracting the population term from both sides of Equation 1 would, of course, result in the same set of results. We prefer presenting population as a control because this way of writing the model facilitates discussing the population's direct effect on total emissions.

[10] Parameter γ measures the change in $CO2$ resulting from a change in ws keeping GDP and total population constant. Having GDP enter as a control ensures the estimated relationship between ws and $CO2$ reflects a shift to a more, or less, pollution intensive form of consumption or production, and not simply a change in the level. Holding population constant means that γ captures the change in CO_2 emissions due to the distribution of ages within a country, and not due to a change in total population.

Ordinary Least Squares

OLS estimation of Equation 1 results in a γ estimate of 3.47 (column 1 in Table 2).[11] We report robust standard errors clustered by country throughout the paper because the residuals suffer from heteroskedasticity across countries and serial correlation within countries. The majority of the variance in CO_2 emissions occurs across countries rather than across time.[12] Thus, in order to reduce the bias on the estimate of the standard error, we cluster by country. The adjusted standard error for the OLS estimate of γ equals 1.20.

The OLS estimate is big, statistically significant at the 1% level, and likely biased downward. Immigration by young workers into countries with high CO_2 emissions, possibly related to consumption or production opportunities, could reduce ws mechanically and decrease the OLS γ estimate.[13] Factors affecting both CO_2 output and mortality contemporaneously, such as increased electricity access, could bias the OLS estimate. Classical measurement error in the variables also could bias the OLS estimate toward zero. Hence, we pursue an instrumental variables strategy.

Two Stage Least Squares (2SLS)

We instrument for the working share with lagged birth rates, where the birth rate is the number of births per 1000 people. Equation 1 still captures the relationship of interest, and Equation 2 is the associated first stage:

$$ws_{st} = \alpha_i + \beta_t + \lambda_1 birth10_{i,t} + \lambda_2 birth20_{i,t} + \lambda_3 birth30_{i,t} + \lambda_4 birth40_{i,t} + controls_{i,t}\delta + \nu_{i,t}. \quad (2)$$

[11] The R^2 equals 0.996; the year and country fixed effects account for most of the variation.

[12] The larger variance in emissions across countries relative to that across time is evident in Figures 1 and 2. Further, we ran a simple two dimensional random effects model to decompose the variance by country and year; this decomposition also indicated that country differences are the relatively large component of the variance in CO_2.

[13] The bias would go the other way if the opportunities related to CO_2 disproportionally attracted prime age workers. Usually, though, young workers migrate most.

The instrumental variables $birth10$ - $birth40$ equal the birth rates in country i 10, 20, 30, and 40 years before year t. All other variables are defined as before. The estimation is by 2SLS.

The 2SLS estimate of the working share's effect on CO_2 (γ) equals 6.17 with standard error 1.87 (Column 2 in Table 2). Table 6 reports the coefficient estimates for the control variables. The baseline 2SLS γ estimate represents our main result. A null hypothesis of no effect can be rejected with better than 99% confidence. A Hausman test rejects equivalence between the OLS and 2SLS coefficient estimates.

The baseline estimate is quantitatively large. Consider the overall increase in CO_2 emissions from 1990 to 2006 within the sample (about 0.29 log points in Table 1). Then, taking the γ estimate literally, the observed increase in the average working share (about 2.7 percentage points in Table 1) accounts for a $2.7\% \times 6.17 \approx 0.17$ log point increase in CO_2 emissions for the average country in the sample, or approximately 60% of the actual increase. A 90% confidence interval for the baseline estimate of γ goes from about 3 to 9, and in some of the robustness checks the point estimate is smaller than the baseline. However, even at a γ value of 3, the working share's impact on emissions is large.

Naturally, the working share depends on lagged birth rates. The F-statistic for the joint significance of the instruments in the first-stage regression (Equation 2) equals 10.63. Weak instruments can cause bias in the 2SLS estimates.[14] Although the sample size is small, the strong first stage mitigates the concern about finite-sample bias problems (Bound, Jaeger,

[14] A rule of thumb often considered is that an F-statistic below 10 indicates possible weak instruments, which makes our instruments seem borderline weak. However, as a Referee pointed out to us, Stock and Yogo (2005) argue that the threshold should depend on the number of exogenous instrumental variables. According to Stock and Yogo, a null of weak instruments can be rejected if the Cragg-Donald statistic exceeds 16.85 in the case of four exogenous instruments. We obtain a value of 117, and the null can be rejected with greater than 95% confidence. Further, we have re-estimated our model using LIML, which is not as affected by weak instruments, obtaining nearly idential results as the baseline. Finally, the instruments are jointly significant in the reduced form regression (Table 3), providing additional evidence that the instruments are not weak. Throughout the rest of the paper, we continue to report the more standard F-statistic.

and Baker 1995). According to Stock and Staiger (1997), the small sample bias in the 2SLS estimate approximately equals $1/(1+\mathrm{F}) \approx 0.09$ percent.[15]

With four instruments, $birth10$ - $birth40$, and a single endogenous variable, ws, the model is overidentified. The p-value for the J-statistic test of the overidentifying restrictions equals 0.51, so the model cannot be rejected.[16] The first stage point estimates have a simple interpretation (Table 3, row 1). A 1.0 percentage point increase in the birth rate 10 years earlier implies about a 0.91 percentage point decrease in the current working share. Sensibly, the coefficient estimates on the birth rates ten, twenty, and thirty years ago have negative signs, and the coefficient for the birth rate forty years ago is positive.

The reduced form regression of CO_2 on the birth rate instruments has the same pattern (Table 3, row 2) as in the first stage regression. We take this pattern as an indication that different age groups consume (and / or produce) goods with different carbon footprints. This pattern also provides additional evidence supporting the exogeneity of the instruments, particularly with respect to GDP. If past GDP levels affected birth rates (e.g. high income countries exhibit low birth rates) and current CO_2 emissions, then the instruments would not be exogenous. However, under this scenario, the birth rates should all have the same sign (negative) in the reduced form regression. Note though, the coefficients on the birth rates lagged ten, twenty, and thirty years are negative, while lag forty is positive (the pattern consistent with our age distribution based hypothesis). Thus, the coefficient pattern is an indication that past GDP levels do not contaminate the exogeneity of the instruments.

[15] The sample is smaller in some of the robustness checks below, and the F-statistic falls. These 2SLS estimates could have additional bias, but even the OLS estimates are large and highly statistically significant. The F-statistic is often higher for the regressions based on larger samples.

[16] The p-value for the J-statistic drops below 0.10 in some of the robustness checks in which the sample size has been reduced.

Robustness Checks

Several countries in the sample agreed to the Kyoto Protocol and committed to reducing their annual CO_2 emissions by about 5% on average. The first robustness check adds a dummy variable for whether a country had ratified the Kyoto Protocol by the given year. Only Annex I (developed) countries are flagged. Most countries entering into Kyoto had ratified by 2002, but variation exists. Column 3 of Table 2 contains the results; the γ estimate (6.05) remains about the same as the baseline.[17] Interestingly, the coefficient on the Kyoto flag (not reported in Table 2), while not statistically significant, equals -0.05, indicating a 5% decline in emissions on average for the 25 Annex I countries.

To keep the panel balanced, countries with only a few observations were omitted from the baseline sample. We worried that including these countries might introduce selection bias or outliers that would affect the estimates. In particular, the baseline sample does not include Germany, Brazil, Russia, India, or China, some of the world's largest CO_2 emitters.[18] Table 2, column 4 reports the results with the 26 observations available on these five countries included.[19] The γ estimate (5.96) stays close to the baseline. Column 5 also includes the Kyoto flag. Again, the γ estimate (5.83) is close to the baseline. Neither the additional countries nor the Kyoto Protocol flag alter the main finding.

According to Aguiar and Hurst (2010), consumption peaks for some goods during the $35-49$ age range, our working share. Consumption (or production) related to CO_2 emissions could peak at a different age range. In Table 4, column 2 the share of $30-34$ year olds has been added to ws. The first-stage F-statistic increases, but the γ estimate decreases to 5.17.

[17] All robustness checks include the controls from the baseline regression, except where noted. The associated OLS, first-stage, and reduced form regressions look similar to the baseline.

[18] Harbaugh et al. (2002) show that some of the evidence on the environmental Kuznets curve is sensitive to the sample selection, covariates included, etc., which is one reason we report a large number of robustness checks.

[19] Germany, Russia, and China are also interesting because they are major carbon trading nations. Their inclusion, however, does not alter the results. Below, we discuss removing Japan, another carbon trading country, from the sample. Again, the main finding remains unchanged.

Column 3 includes the $50-54$ age group in ws instead. The point estimate increases to 6.51, but the first-stage F-statistic falls. Additional age groups are added as regressors in column 4. The new explanatory variables are instrumented as before, and the first stage regressions (not reported) remain strong. To avoid collinearity, the young group (age 0-19) is omitted. Thus, the coefficient estimates measure movement out of the young group into each other group. The point estimate (5.92) on the working share remains statistically different from zero at the 1% level. We tried broader age groups and finer age groups, and the results stay close to the baseline.[20]

Table 5 reports the results when eleven more years (1939-1949) of lagged birth rate information from previous Demographic Yearbooks are included for some countries. If a country does not have data for any year, then the country is dropped entirely from the sample.[21] The new balanced panel has 35 countries. Column 1 reports the baseline regression from 1990-2006 with the smaller sample of countries. The γ estimate falls to 4.35. Column 2 reports the results including the 1979-1989 data. The coefficient estimate equals 4.07.[22] However, since CO_2 emissions in the new sample grew slowly during the 1980s, the change in ws actually explains a larger portion of the increase in CO_2 emissions from 1979 to 2006 in the 35 countries (using γ equal to 4.07) than from 1990-2006 in the full 46 countries (using γ equal to 6.17). In column 3, we use the new data to instrument for the working share with the birth rate lagged 49 years in addition to lags of 10, 20, 30, and 40 years.[23] The γ estimate (4.28) is virtually identical to the baseline (4.35).[24] We also report the analysis

[20] We also tried using the total (logged) number of people in the 35-49 age group rather than the share. The first stage F-statistic increases, and the γ estimate remains quantitatively large and statistically significant at the 1% level.

[21] The Appendix lists the countries and describes why the older birth rates might be less reliable.

[22] The statistical significance decreases somewhat, but the number of countries to cluster on has fallen below 42, making clustered standard errors less reliable (Angrist and Pischke 2008). Using Newey-West lag 2 standard errors, the estimates continue to be statistically significant at the 1% level in all cases.

[23] We also used birth rates lagged 49 years as an instrument with the additional age groups from Table 4, obtaining similar results.

[24] We also have instrumented for the working share with the sum of the birthrates 35-49 years ago, similar to Lugauer (2012). The coefficient estimate increases to 4.84.

including all the countries in column 4. The γ estimate when the panel is not balanced equals 5.11.[25] Column 5 includes the observations for Germany, Brazil, Russia, India, and China, bringing the sample size to 1299. The first stage F-statistic equals 13.48. The working share effect equals 5.16, and it is statistically significant at better than the 1% level. Overall, the additional birth rate data does not alter the main finding.

Table 6 reports estimates for the control variable coefficients in Equation 1. Column 1 repeats the baseline. Total population and GDP are positively correlated with CO_2 emissions. The square of GDP is negatively related, indicating an environmental Kuznets curve type relationship; although, CO_2 emissions do not begin to decrease until a country achieves high GDP levels. We tried several variations of the controls, and the γ estimate does not change appreciably.[26] None of the controls are individually statistically different from zero in the baseline regression.

Next, we add four controls into equations 1 and 2. The new variables are the proportion of the labor force working in industry (as opposed to services or agriculture), the level of exports and imports in logs, and the proportion of electricity produced using coal. The industry term represents an attempt to account for the concentration of manufacturing production. Controlling for the level of imports and exports helps ensure that the observed correlation reflects a domestic phenomenon.[27] We include the coal variable because coal is among the dirtiest ways to produce electricity in terms of CO_2 emissions. The country fixed effects account for the time-invariant levels of these variables; however, a country with an increasing supply of younger workers might begin to generate power via more labor intensive

[25] Columns 4 and 5 include a few observations from 2007. Dropping the 2007 data does not change the estimates by much.

[26] For example, some of the environmental Kuznets curve literature uses logged GDP per capita instead of total GDP. When we control for GDP and GDP squared per capita and drop the population variable, the γ estimate increases to 7.39.

[27] Controlling for total imports and exports does not address the types of goods traded. As populations age, they may change the mix of goods traded or engage in pollution off-shoring. See Antweiler, Copeland, and Taylor (2001) and Kahn (2003) for more on the pollution haven hypothesis.

methods such as coal, or export more, or manufacture more. The World Bank's World Development Indicators has complete data for 29 of the countries in our sample. Using the smaller set of countries, the baseline γ estimate decreases to 4.46, with a relatively lower first stage F-statistic (Table 6, column 2). Including the four additional controls leads to a larger γ estimate (4.84), but still a weak first stage (Table 6, column 3). Column 4 reports the results with an unbalanced sample, and the results remain similar. Each of the new controls has a sizable effect on CO_2 emissions, but only coal is statistically significant. We tried other controls for the method of production; none altered the main finding. We view the estimates in Table 6 as evidence that life-cycle consumption patterns rather than production methods drive the baseline results.

We have searched for specific countries, outliers, or other odd patterns affecting the results. We omit the full details to save space, but a few of the checks are worth mentioning. Japanese CO_2 emissions take only two values in Figure 2, so we ran the regressions without Japan. We also tried dropping the United States, as its emissions dwarf all other countries besides China. In both cases, the γ estimate increases relative to the baseline. We dropped the six largest countries by population and separately the six smallest, and also weighted all observations by population. The estimates are smaller than the baseline, but quantitatively large (ranging from 4.7 to 5.8) and statistically significant. We ran the regressions swapping each country's demographic data with the next country alphabetically as a falsification check of completely spurious correlation. The γ estimate is -0.59 and not statistically different from zero. We examined the residuals from the first stage regression, most of the largest residuals come from Japan and Singapore. Dropping Japan and Singapore increases the first stage F-statistic to 11.64 and leaves the γ estimate virtually unchanged from the baseline. We also examined the residuals from the second stage, finding no other patterns by country or year.

Much of the world's man-made CO_2 emissions comes from electricity production, so in column 1 of Table 7 the dependent variable has been replaced by logged total electricity generation.[28] Belize and Fiji are dropped from the sample due to lack of information. The γ estimate remains statistically different from zero, indicating that the age distribution affects electricity production. The first stage, OLS, reduced form, and parameter estimates on the controls are similar to the baseline.

The remainder of Table 7 reports γ estimates when each variable has been fifth differenced. For example, $CO2_{it}$ in Equation 1 has been replaced with the log of total CO_2 emissions in year t minus the emissions in year $t-5$. We use long differences to eliminate year-to-year variation in the data that is independent of long term population changes.[29] Another reason to difference the data, as pointed out in Cole and Neumayer (2004), is non-stationary variables can lead to poor estimates.[30] The main explanatory variable, the working share of the population, is probably stationary by construction. The control variables and emissions of CO_2 could have unit roots, although $CO2$ does not appear to for most countries in Figure 2. Differencing helps ensure stationarity, and differencing eliminates the country fixed effects and five years of observations. The 2SLS γ estimate (5.25 in column 3) based on the differenced variables is statistically significant at the 1% level.[31] As in the baseline, the 2SLS estimate of the working share effect exceeds the OLS estimate (3.10 in column 2). Also, the p-value for the J-statistic test of the overidentifying restrictions equals 0.70, so the model specification cannot be rejected. Column 4 includes the observations from Germany, Brazil, Russia, India, and China, and the γ estimate (5.08) is similar to column 3.

[28] The magnitude of the coefficient estimates in Table 7 should not be directly compared because the left hand side variable is different.

[29] As can be seen in Figure 2, CO_2 emissions frequently deviate from trend; whereas, the working share moves smoothly. Demographic changes probably only explain the low frequency movements in $CO2$. We also tried altering $CO2$ by explicitly removing the high frequency deviations from trend with the Hodrick-Prescott filter (smoothing parameter 6.25), and the estimate for γ increases to 6.59.

[30] We looked for evidence of unit roots at lag one using standard panel data tests. In each case, the null of a unit root could be strongly rejected for both the working share and CO_2 variables.

[31] A regression in levels using years 1995-2006 results in a γ estimate of 5.81.

Overall, the main result - the age distribution's large effect on CO_2 emissions - survives the many robustness checks. The γ estimate is sometimes smaller than the baseline, but the working share effect remains quantitatively important and statistically significant in all cases.

Discussion

As mentioned, we think life-cycle consumption patterns underlie the age distribution effect. However, even with the robustness checks in Table 6, our approach cannot rule out the production side. In part, the distinction is semantics. Power generation and transportation create most CO_2 emissions and are both used as inputs into production and consumption. Still, countries could adopt different production techniques (machines, factory locations, power sources, etc.) as the age distribution (and labor supply) evolves without changing the goods consumed. Similarly, different industries might thrive in countries with different labor forces, with trade keeping consumption patterns unchanged (e.g. pollution off-shoring). The age distribution could also impact environmental policy (Kahn 2002). Since we cannot rule out these competing explanations, we conclude that more research is needed on the theoretical mechanism linking the age distribution to CO_2 emissions.

Automobile use (which could be consumption or an input to production) varies by age. For example, the US National Household Travel Survey (2011) reports that prime working age individuals drive the most on average.[32] Changes in a population's age structure might generate changes in the aggregate amount of driving. Since burning fuel creates CO_2 emissions, motor vehicles could be the mechanism connecting the age distribution to emissions. We were unable to locate time series data to control for automobile use by country (and it is not clear that we should - this is the type of effect we want to measure); however, if other

[32] Drivers aged 35-54 logged twice as many miles per year compared to teenagers and retirees in 2009, and the amount of driving per driver has been about constant since 1990.

countries have life-cycle driving patterns similar to the US, then motor vehicle use might help explain our results.

Since current driving habits do not directly effect past fertility decisions, the omission of automobile data does not undermine our 2SLS estimation strategy. However, a violation of the exclusion restriction is impossible to fully rule out, even though omitted variables that resemble the pattern implied by the birth rates are difficult to think of. Past business cycle fluctuations or a country's level of development could be two possibilities. Fertility decisions probably change over the cycle, and current CO_2 emissions might be related to past GDP fluctuations (a tenuous connection, perhaps). To some extent the regressions have already controlled for this link. Every regression includes logged GDP and Table 7 reports the results when the GDP data has been differenced. We also have tried adding past GDP growth rates as covariates in both the first and second stage regressions. For example, adding the 10-year lag of GDP growth results in a γ estimate of 6.05. We also tried other lags and using GDP per capita growth rates; the results never strayed far from the baseline estimate.

Explicitly controlling for the notion of development is more difficult. The fertility rate itself is sometimes taken as a measure of development (thus, our story might in this way be related to development), as is GDP, GDP growth, population growth, and electricity production. We have already considered these variables in the various specifications of the model. Plus, all the regressions include (time invariant) country fixed effects, and we also conducted the experiment with the Kyoto protocol flag (which possibly could be interpreted as a time varying indicator of development). Also, much of the sample consists of already developed countries. We also ran regressions including the amount of new investment per year (yearly capital investment from the Penn World Tables) and (separately) using the total number of births for an instrument rather than the live birth rate. To save space, the full results are not reported. In each case the estimates remain largely unchanged, and we continue to see an increase in the point estimate on ws when we move from OLS to 2SLS. Thus, we do not believe that the correlation between birth rates and a country's level of development (and subsequent CO_2 emissions) is behind our results, except working through the age distribution channel.

Finally, we return to the overall importance of our findings. The magnitude of the working share effect is about equivalent to the effect of GDP and total population. Although we have not focused on forecasting CO_2 emissions, some quick forward looking calculations help put the results into perspective. Imagine a (developed) country with projected annual growth rates of 2% for GDP and 0.7% for total population and a -0.3 percentage point annual decrease for the working share. Ignoring the environmental Kuznets curve and holding all else constant, the regression results imply that the shrinking working share (leading to a 1.8% annual reduction) erases the growth in emissions due to output (1.4% annual increase) and population (0.4% annual increase) combined.

For most developing countries changes in the age distribution will *contribute* to the growth of CO_2 emissions. Using United Nations age distribution projections in conjunction with the regression results, Table 8 lists the percent change in annual CO_2 emissions versus 2006 levels due solely to changes in the working share. Developing regions, excluding China, will have increasing working shares for the next twenty years, followed by gradual decline.[33] Emissions in India, the world's third largest CO_2 producer, will increase by 20% over the next two decades due to demographic changes alone. The working share in developed regions will decline for the foreseeable future, reducing annual emissions more than 30% by 2041. China, the world's largest CO_2 producer, should see a reduction in emissions, but not for another

[33] As the fraction of the population in their prime working years increases, GDP should increase, and, according to proponents of the environmental Kuznets curve, CO_2 emissions might actually begin to decrease. However, the change in the age distribution associated with such GDP growth increases CO_2 emissions, working against the GDP effect. Thus, our results provide a possible explanation for why studies of CO_2 emissions and the environmental Kuznets curve have had mixed results. See Lieb (2004), Dinda (2004), and Bartz and Kelly (2008) for more on the environmental Kuznets curve.

30 years. Emissions in the US, the second largest producer, should begin to fall immediately. These calculations are obviously rough because they are outside of our sample and do not consider the many other factors affecting emissions; however, Table 8 again demonstrates that the age distribution has a large effect on CO_2 emissions.

4 Conclusion

The potential for widespread disaster has prompted most nations to consider regulations aimed at curbing CO_2 emissions. Such regulation often trades current and future consumption for lower emissions. Thus, understanding the determinants of CO_2 emissions has become increasingly important.

We have documented a statistically and economically significant relationship between the share of prime working age individuals within a country and CO_2 emissions, finding that a one percentage point increase in the working share results in as much as a 6.1% increase in CO_2 emissions. The estimates can account for a large portion of the increase in CO_2 between 1990 and 2006 in our sample of countries.

As discussed in the Introduction, the relationship between the age distribution and emissions may not, in itself, suggest any particular policy for global CO_2 reduction. However, this relationship could impact the optimal strategies for individual countries in international climate negotiations. Moreover, a better understanding of the life cycle determinants of pollution might generate insights that could inform policies aimed at reducing emissions. Therefore, we believe future research should be aimed at uncovering why the age distribution has such a large effect on CO_2 emissions, and forecasts of future CO_2 emissions should take the age distribution effect into account.

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5 Appendix: Data Sources

Annual country specific data on CO_2 emissions, real GDP (in 2000 dollars), imports, exports, electricity production and several other variables were extracted in June of 2011 from the World Bank World Development Indicators web site:

data.worldbank.org.

Some sources report CO_2 emissions in kilotons of carbon or CO_2 equivalents; we use kilotons of actual carbon-dioxide. Measurement of CO_2 emissions is being constantly refined. The World Bank estimates include only man-made sources, but not sea ships. Military bases count toward the geographic location, not the home country. The Carbon-Dioxide Information Analysis Center generated the CO_2 estimates for the World Bank, and more details of the estimation methodology can be found on their web site:

cdiac.ornl.gov.

The age distribution information comes from the United Nations World Population Prospects (2008 Revision). Birth rates from 1950 to 1996 come from Table 1 and Table 5 of the United Nations 1997 Demographic Yearbook, available at this web site:

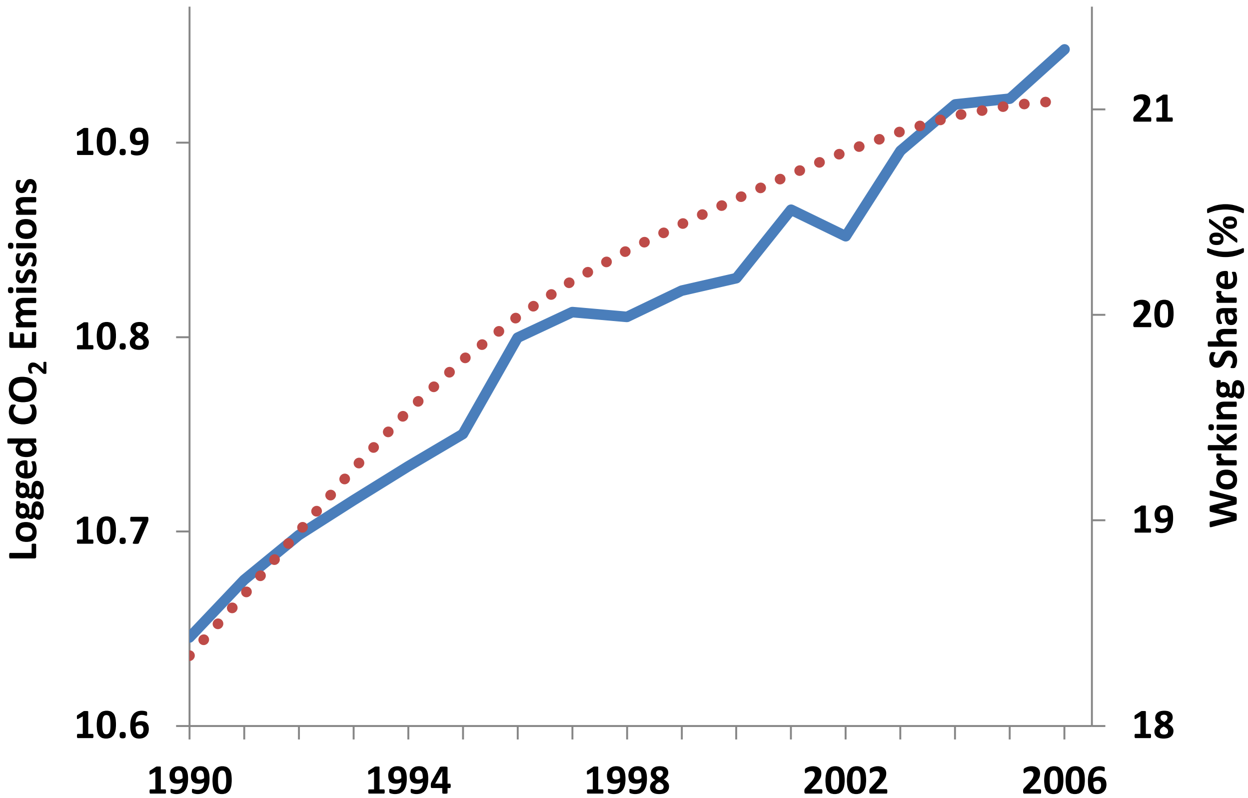
unstats.un.org/unsd/demographic/products/dyb/dybhist.htm.

Single missing observations were imputed by averaging adjacent entries. Countries missing multiple observations in sequence (e.g. Argentina and the Phillippines) were dropped from the sample. The 1997 Demographic Yearbook also contains birth rates from 1948, 1949, and 1997 for some countries in the baseline sample. Including the extra data increases the γ estimate to 6.79. The robustness checks experiment with including birth rates as far back as 1939 from the United Nations 1954 Demographic Yearbook, available at this web site:

unstats.un.org/unsd/demographic/products/dyb/dybsets/1954%20DYB.pdf.

When using the birth rates from the 1954 Demographic Yearbook the following eleven countries are dropped: Belize, Bulgaria, Iran, Israel, Panama, Poland, Romania, Singapore, Sri Lanka, Tunisia, and Uruguay. The older birth rates may be less reliable because some countries reported registered births in some years rather than actual births, other countries did not count European births, and changes in geographic boundaries were not accounted for. Also note the following issues with the lagged birth rates. Singapore's birth rates only reflect the population on the island of Singapore before 1947. Ecuador's birth data is missing for several provinces, but the birth rate is calculated using the population of the entire country, resulting in an underestimation of the birth rate. Hungary's birth rates prior to 1947 include information from territory ceded to Czechoslovakia. Romania's birth rates include information from territory later given up. Re-doing the baseline regressions without these four countries results in a γ estimate of 5.17, which is statistically significant at the 1% level.

FIGURE 1
Average CO_2 Emissions and Working Share, 1990-2006



Notes: Figure 1 plots average total logged carbon-dioxide emissions (solid line) and the average working share (dotted line) by year for the 46 countries in our baseline sample.

FIGURE 2
CO_2 Emissions and Working Share by Country, 1990-2006

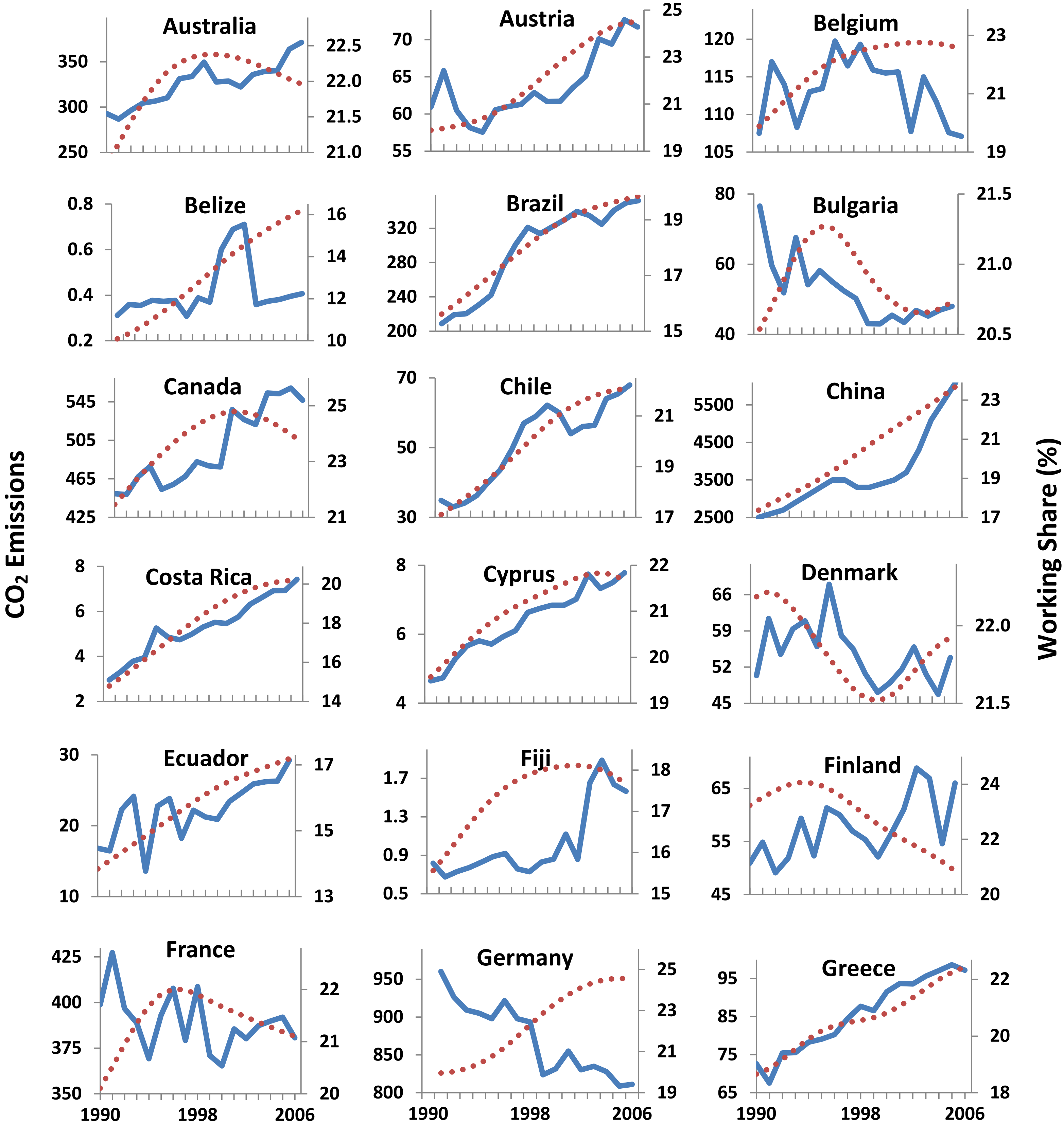


FIGURE 2

CO_2 Emissions and Working Share by Country, 1990-2006 (continued)

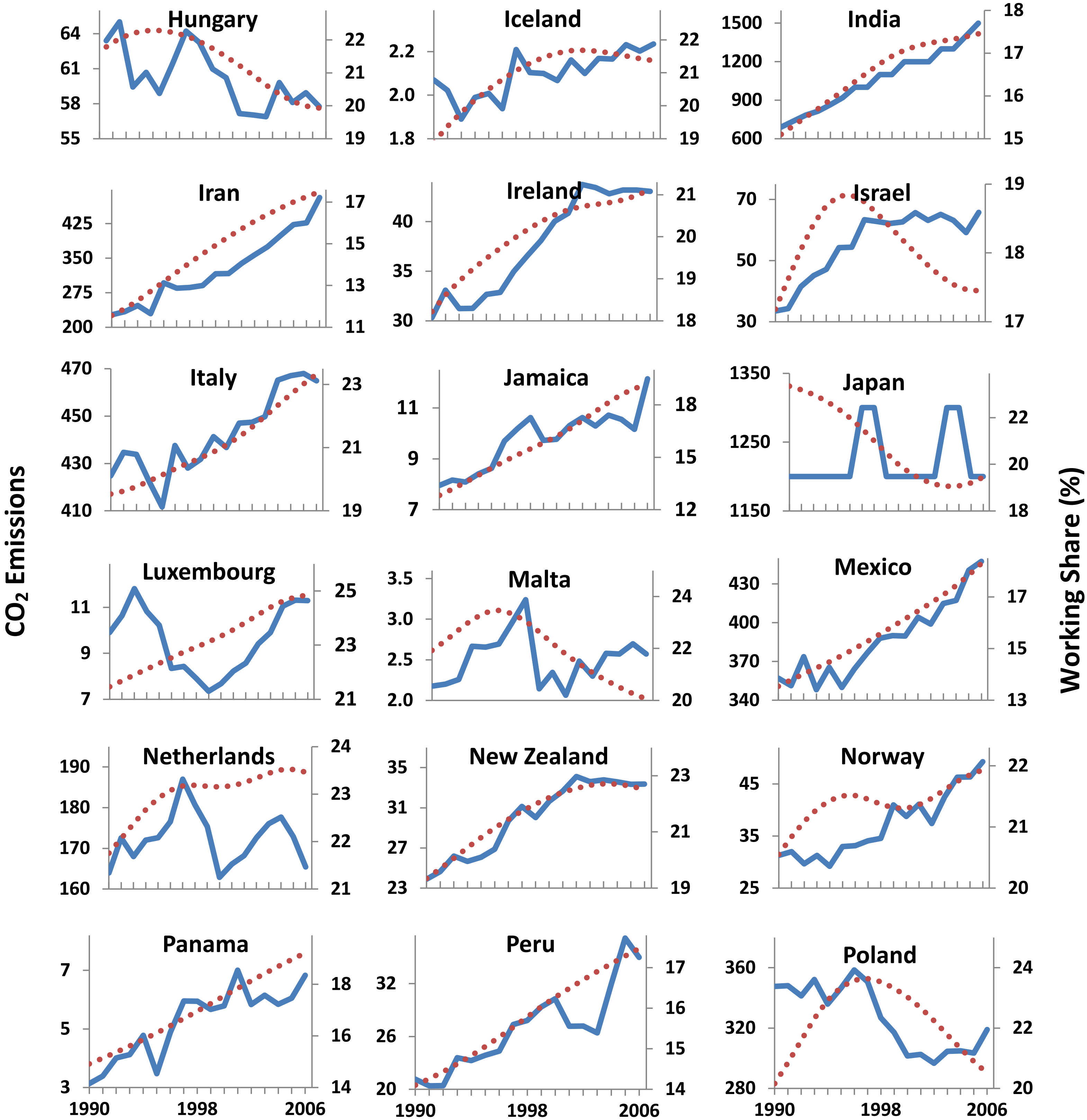
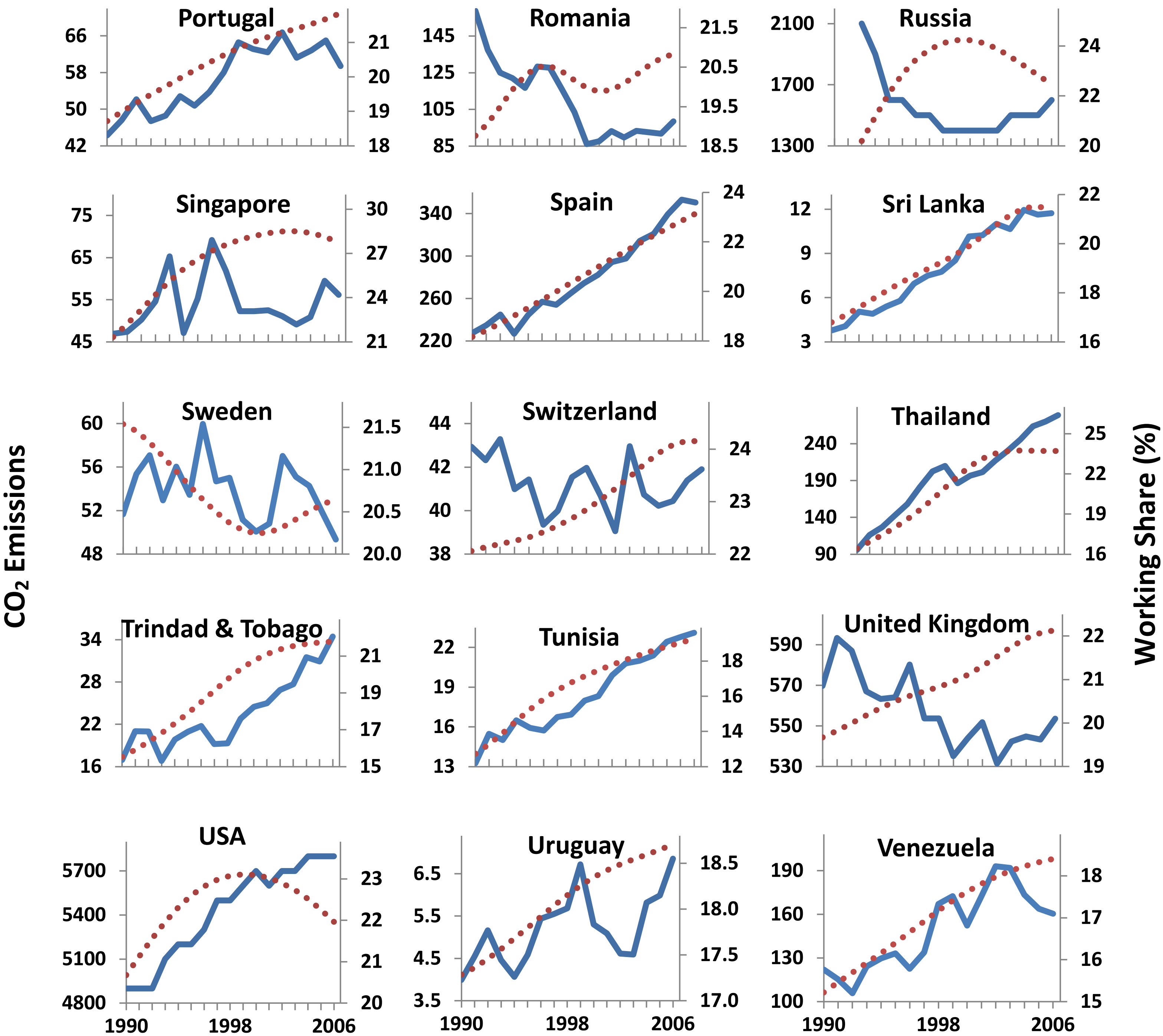


FIGURE 2

CO_2 Emissions and Working Share by Country, 1990-2006 (continued)



Notes: Figure 2 plots total kilotons of carbon-dioxide emissions (solid line) and the working share (dotted line) by year for each of the 46 countries in the baseline sample plus Germany, Brazil, Russia, India, and China.

TABLE 1
Variable Averages across Countries, 1990-2006

Variable	All Years	1990	2006
log Total CO_2 Emissions (*CO2*)	10.81	10.65	10.94
	(1.91)	(1.99)	(1.87)
Working Share (*ws*)	20.08%	18.34%	21.04%
	(2.97%)	(3.29%)	(2.35%)
log Total GDP	25.05	24.81	25.33
	(1.95)	(2.01)	(1.93)
log Total Population	9.07	8.99	9.14
	(1.63)	(1.66)	(1.63)
Countries	46	46	46
Observations	782	46	46

Notes: This table reports means for the main variables across the 46 countries in the baseline sample with standard errors in parentheses.

TABLE 2

Estimates of the Working Share's Effect on CO_2 Emissions, 1990-2006

	Working Share (*ws*)				
	OLS (1)	Baseline 2SLS (2)	Kyoto (3)	G BRIC (4)	Kyoto G BRIC (5)
log CO_2 Emissions (*CO2*)	3.47 (1.20) ***	6.17 (1.87) ***	6.05 (1.47) ***	5.96 (1.77) ***	5.83 (1.76) ***
F-statistic	-	10.63	10.29	11.01	10.68
Countries	46	46	46	51	51
Observations	782	782	782	808	808

Notes: This table reports estimates for the parameter γ in Equation 1 with standard errors clustered by country in parentheses. The F-statistic tests the joint significance of the instruments in the first stage regression based on Equation 2. The regressions include country and year fixed effects and logged GDP, GDP squared, and total population as controls. Stars denote statistical significance of the parameter estimate at the * 10%, ** 5%, and *** 1% level.

TABLE 3

First Stage and Reduced Form Estimates, 1990-2006

	Birth Rates					
	Lag 10	Lag 20	Lag 30	Lag 40	R^2	Observations
Working Share (*ws*) age 35-49	-0.910 (0.259) ***	-0.431 (0.385)	-1.791 (0.383) ***	1.424 (0.313) ***	0.951	782
log CO_2 Emissions (*CO2*)	-7.050 (4.012) *	-3.835 (4.396)	-8.356 (4.531) *	9.907 (4.099) *	0.997	782

Notes: Row 1 reports the OLS coefficient estimates for instruments in the first stage regression (λ_1–λ_4 in Equation 2) and row 2 reports the reduced form of the 2SLS. The estimates have been multiplied by 1000. The regressions include country and year fixed effects and logged GDP, GDP squared, and total population as controls. Standard errors clustered by country are in parentheses. Stars denote statistical significance of the parameter estimate at the * 10%, ** 5%, and *** 1% level.

TABLE 4

2SLS Estimates of the Working Share's Effect on CO_2 Emissions, Robustness Checks

	log CO_2 Emissions (*CO2*)			
	Baseline (1)	Include 30-34 (2)	Include 50-54 (3)	More Age Groups (4)
Working Share (35-49)	6.17	5.17	6.51	5.92
	(1.87) ***	(1.47) ***	(1.94) ***	(2.16) ***
Young Workers (20-34)	-	-	-	-0.395
				(2.19)
Older Workers (50-69)	-	-	-	-3.846
				(8.47)
Old (70 +)	-	-	-	5.06
				(15.33)
F-statistic	10.63	15.99	10.24	-
Years	1990-2006	1990-2006	1990-2006	1990-2006
Countries	46	46	46	46
Observations	782	782	782	782

Notes: This table reports 2SLS estimates for Equation 1 with standard errors clustered by country in parentheses. The F-statistic tests the joint significance of the instruments in the first stage regression based on Equation 2. The regressions include country and year fixed effects and logged GDP, GDP squared, and total population as controls. Stars on the standard errors denote statistical significance of the parameter estimate at the * 10%, ** 5%, and *** 1% level.

TABLE 5

2SLS Estimates of the Working Share's Effect on CO_2 Emissions, Additional Data

	Working Share (*ws*)				
	Baseline Fewer Countries (1)	Include 1979-1989 (2)	Instrument Lag 49 (3)	Unbalanced (4)	Unbalanced G BRIC (5)
log CO_2 Emissions (*CO2*)	4.35	4.07	4.28	5.11	5.16
	(1.49) ***	(1.84) **	(1.41) ***	(1.58) ***	(1.57) ***
F-statistic	10.35	13.30	13.54	14.15	13.48
Countries	35	35	35	46	51
Years	1990-2006	1979-2006	1990-2006	1979-2007	1979-2007
Observations	595	980	595	1269	1299

Notes: This table reports estimates for the parameter γ in Equation 1 with standard errors clustered by country in parentheses. The F-statistic tests the joint significance of the instruments in the first stage regression based on Equation 2. The regressions include country and year fixed effects and logged GDP, GDP squared, and total population as controls. Stars denote statistical significance of the parameter estimate at the * 10%, ** 5%, and *** 1% level.

TABLE 6

2SLS Estimates of the Working Share's Effect on CO_2 Emissions, Robustness Checks, 1990-2006

	log CO_2 Emissions (*CO2*)			
	Baseline (1)	Fewer Countries (2)	Additional Controls (3)	Unbalanced (4)
Working Share (*ws*)	6.17	4.46	4.84	4.77
	(1.87) ***	(1.65) ***	(1.31) ***	(1.37) ***
log GDP	0.678	0.957	1.236	2.467
	(1.291)	(0.764)	(0.750) *	(1.176) **
log GDP^2	-0.009	-0.009	-0.011	-0.043
	(0.027)	(0.016)	(0.014)	(0.023) *
log Population	0.599	1.324	0.882	0.950
	(0.492)	(0.213) ***	(0.251) ***	(0.415) **
log Exports	-	-	0.025	0.012
			(0.085)	(0.057)
log Imports	-	-	-0.093	-0.129
			(0.068)	(0.069)*
Prop Industry	-	-	0.004	0.011
			(0.005)	(0.009)
Prop Coal	-	-	0.005	0.004
			(0.001) ***	(0.001) ***
F-statistic	10.63	4.97	4.98	7.65
Countries	46	29	29	43
Observations	782	493	493	664

Notes: This table reports estimates for the parameter γ in Equation 1 with standard errors clustered by country in parentheses. The F-statistic tests the joint significance of the instruments in the first stage regression based on Equation 2. Stars denote statistical significance of the parameter estimate at the * 10%, ** 5%, and *** 1% level.

TABLE 7
Estimates of the Working Share's Effect on CO_2 Emissions, Further Robustness Checks

	Working Share (*ws*)			
	Total Electricity (1)	5^{th} Difference OLS (2)	5^{th} Difference 2SLS (3)	5^{th} Dif 2SLS G BRIC (4)
log CO_2 Emissions (*CO2*)	5.49	3.10	5.25	5.08
	(1.59) ***	(1.02) ***	(2.06) ***	(1.96) ***
F-statistic	12.21	-	7.85	8.38
Years	1990-2006	1995-2006	1995-2006	1995-2006
Countries	44	46	46	51
Observations	748	552	552	566

Notes: This table reports estimates for alternative specifications to Equation 1 with standard errors clustered by country in parentheses. The F-statistic tests the joint significance of the instruments in the first stage regression based on Equation 2. Stars denote statistical significance of the parameter estimate at the * 10%, ** 5%, and *** 1% level.

TABLE 8

Implied Percent Change in Annual CO_2 Emissions from 2006 Levels, 2011-2100

	2011	2021	2031	2041	2051	2075	2100
Developing Regions (excluding China)	2.9	11.3	17.0	14.6	13.4	7.3	2.8
Developed Regions	-4.9	-10.5	-18.3	-31.7	-30.5	-34.7	-36.9
China	8.5	-11.0	-7.2	-26.9	-39.8	-51.1	-49.6
USA	-10.9	-19.4	-20.0	-26.2	-25.6	-30.4	-35.6
India	3.3	13.1	21.2	20.7	18.6	6.8	-4.5

Notes: This table reports the projected percent change in annual carbon-dioxide emissions due solely from changes in the working share. The estimates are based on the baseline regression results and United Nation age distribution forecasts.