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# The effect of urbanization on $CO_2$ emissions in emerging economies

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ABSTRACT

The theories of ecological modernization and urban environmental transition both recognize that urbanization can have positive and negative impacts on the natural environment with the net effect being hard to determine a priori. This study uses recently developed panel regression techniques that allow for heterogeneous slope coefficients and cross-section dependence to model the impact that urbanization has on $CO_2$ emissions for a panel of emerging economies. The estimated contemporaneous coefficients on the energy intensity and affluence variables are positive, statistically significant and fairly similar across different estimation techniques. By comparison, the estimated contemporaneous coefficient on the urbanization variable is sensitive to the estimation technique. In most specifications, the estimated coefficient on the urbanization variable is positive but statistically insignificant. The implications of these results for sustainable development policy are discussed.



## 1. Introduction

The year 2010 marked a milestone in urbanization as this was the year that world urbanization passed 50%.[1] While urbanization in developed countries continues to increase, developing countries are expected to experience the greatest increase in urbanization. For example, the United Nations Population Division (2007) predicts that in the year 2020, urbanization in the less developed regions of the world will pass 50%. Furthermore, it is expected that urbanization in the less developed regions of the world will more than triple, from 18% in 1950 to 67% in 2050. Changes in urbanization can affect economic growth, energy use and carbon dioxide emissions ($CO_2$). If urbanization has a significant impact on carbon dioxide emissions then this will have implications for sustainable development and climate change policies.

If urbanization is found to have a positive and statistically significant impact on $CO_2$ emissions then this can affect forecasting models and climate change policy. Forecasting models of $CO_2$ emissions that fail to take into account the impact of urbanization on $CO_2$ emissions will under forecast carbon dioxide emissions. Energy and environmental policies that omit the impact of urbanization on $CO_2$ emissions will likely lead to inaccurate outcomes making sustainable development objectives more difficult to achieve. If urbanization is found to have a negative and statistically significant impact on $CO_2$ emissions then this will make sustainable development objectives easier to achieve.

The theories of ecological modernization and urban environmental transition both recognize that urbanization can have positive and negative impacts on the natural environment with the net effect being hard to determine a priori. If urbanization is found to have a statistically insignificant impact on $CO_2$ emissions then urbanization will have no meaningful impact on $CO_2$ emissions. This is consistent with the positive and negative effects of urbanization on $CO_2$ emissions canceling each other out.

This paper makes several important contributions to the literature. First, the relationship between urbanization and carbon dioxide emissions has been studied by a number of authors (eg. Cole and Neumayer, 2004; Hossain, 2011; Liddle and Lung, 2010; Martinez-Zarzoso and Maruotti, 2011; Parikh and Shukla, 1995; Poumanyvong and Kaneko, 2010; Sharma, 2011; York et al., 2003) but most of this research uses a static model applied to a panel data set. A panel data set offers advantages over a cross-section data set by including a time dimension. This increases the number of observations and allows for variation in both the cross-section and time dimension. Static models cannot, however, capture dynamic relationships. Dynamic models are advantageous because both long-run and short-run impacts are modeled. This paper uses a static and dynamic framework to model the impact of urbanization on carbon dioxide emissions in order to compare the results obtained by the two different models.

Second, previous studies have mostly assumed that the impact of urbanization on carbon dioxide emissions is homogeneous across countries. This is a very strong assumption to make and one that is unlikely to hold across a large grouping of countries. In this paper panel regression models are estimated using recently developed

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[1] Data sourced from http://esa.un.org/unup/.

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techniques that allow for heterogeneity in the estimation of the slope coefficients and cross-section dependence. If panel data exhibits cross-section dependence, estimating models with homogeneous slope coefficients (as in the case of pooled OLS, fixed effects, or GMM) may yield estimated coefficients that are biased (Andrews, 2005). In order to account for cross-section dependence, models are estimated using the mean group (MG) estimator of Pesaran and Smith (1995), Pesaran's (2006) Common Correlated Effects Mean Group (CCEMG) estimator, and the Augmented Mean Group (AMG) estimator of Eberhardt and Teal (2010) and Bond and Eberhardt (2009).

The purpose of this paper is to investigate the impact of urbanization on $CO_2$ emissions for a panel of 16 emerging economies. Empirical models are estimated using heterogeneous panel regression techniques. The following sections of the paper set out the contextual material, the empirical model, data, empirical results, implications, and conclusions.

## 2. A brief review of the literature

"Although urbanization is often discussed in the context of economic modernization, it is a demographic indicator that increases urban density and transforms the organization of human behavior, thereby influencing household energy use patterns (Barnes et al., 2005; Poumanyvong and Kaneko, 2010)."

According to Poumanyvong and Kaneko (2010), the existing literature points to three theories (ecological modernization, urban environmental transition and compact city theories) that are useful for explaining how urbanization can impact the natural environment. The theory of ecological modernization details how urbanization is a process of social transformation that is an important indicator of modernization. As societies move from low to middle stages of development, environmental problems may increase because in these stages of development, economic growth takes priority over environmental sustainability. As societies continue to evolve to higher stages of development, environmental damages become more important and societies seek ways to make their societies more environmentally sustainable. The damaging impact of economic growth on the environment may be reduced by technological innovation, urbanization, and a shift from a manufacturing based economy to a service based economy (Crenshaw and Jenkins, 1996; Gouldson and Murphy, 1997; Mol and Spaargaren, 2000).

The theory of urban environmental transition links environmental issues with urban evolution at the city level (McGranahan et al., 2001). In modern history, cities often become wealthier by increasing their manufacturing base and this can lead to industrial pollution problems that impact the land, air and water. As cities continue to become wealthier, industrial pollution problems may be lessened via environmental regulations, technological innovation, or changes in economic sector composition. Wealthier cities create wealthier residents and wealthier residents demand more energy intensive products and this puts further stress on the environment. The net impact of the wealth effect is difficult to determine a priori.

The compact city theory mostly focuses on the benefits of increased urbanization. Higher urban density helps to facilitate economies of scale for public infrastructure (eg. public transportation, water supply, electricity production, schools, hospitals) and these economies of scale lead to lower environmental damages (Burton, 2000; Capello and Camagni, 2000; Jenks et al., 1996; Newman and Kenworthy, 1989).

The empirical relationship between urbanization and $CO_2$ emissions has been studied by a number of authors. In one of the earliest studies, Parikh and Shukla (1995) use a data set of 83 developed and developing countries for the year 1986 to investigate the impact of urbanization on energy use and toxic emissions. They find that urbanization has a positive and significant impact on $CO_2$ emissions, $CH_4$ emissions, and CFC emissions. In particular, they find a $CO_2$ emissions elasticity of urbanization of 0.036. York et al. (2003) use a cross section of 137 countries to test for a relationship between urbanization and $CO_2$ emissions. They find evidence that increases in urbanization lead to increases in $CO_2$ emissions.

Cole and Neumayer (2004) study 86 countries over the period 1975 to 1998 and find a positive relation between urbanization and $CO_2$ emissions. More specifically, they find a 10% increase in urbanization increases $CO_2$ emissions by 7%. For developing countries, Fan et al. (2006) find a negative relationship between urbanization and carbon dioxide emissions. Liddle and Lung (2010), using a panel data set of 17 developed countries followed over 10, 5 year periods, find a positive but insignificant impact of urbanization on carbon dioxide emissions when aggregate carbon dioxide emissions are used as the dependent variable. Urbanization has a positive and statistically significant impact on carbon dioxide emissions when carbon dioxide from transport is used as the dependent variable.

Poumanyvong and Kaneko (2010) use a Stochastic Impacts by Regression on Population, Affluence and Technology (STIRPAT) model to investigate the impact of urbanization on $CO_2$ emissions in a panel of 99 countries over the period 1975 to 2005. A variety of panel regression techniques are used but the empirical approaches are all static in nature. They find that urbanization has a positive and significant impact on $CO_2$ emissions for each income group but its impact is greatest for the middle income group of countries. For all income groups, the estimated coefficient on urbanization varies between 0.350 and 0.506. For low income groups, the estimated coefficient on urbanization varies between 0.430 and 0.615. For middle income groups, the estimated coefficient on urbanization varies between 0.210 and 0.512. For high income groups, the estimated coefficient on urbanization varies between 0.041 and 0.358.

Martinez-Zarzoso and Maruotti (2011) use a STIRPAT model in a panel of 88 developing countries over the period 1975 to 2003. Empirical results estimated using the complete panel of countries supports an inverted U shaped relationship between urbanization and CO2 emissions. From their results reported in Table 2, the estimated coefficient on the urbanization variable is statistically significant at the 10% level and ranges in value between 0.506 and 1.329. The estimated coefficient on the squared urban term varies between −0.089 and −0.209. A novel feature of their paper is the use of a semi-parametric mixture model to classify countries into groupings based on $CO_2$ emissions. Three groups of countries are found and in two of the country grouping, the estimated coefficient on urbanization is statistically significant at 10% and varies between 0.445 and 0.801. This approach is useful in showing that the impact of urbanization on CO2 emissions differs across the country groups providing support to the idea that panel regression models estimated assuming homogenous slope coefficients may give rise to misleading results. A one period lag of $CO_2$ emissions is included in the regression models to account for dynamics.

Sharma (2011) studies a large panel of 69 countries (including high income, middle income and low income countries) and finds that urbanization does have a negative and statistically significant impact on carbon emissions for the global panel. For the global panel, a 1% increase in urbanization decreases $CO_2$ emissions by 0.7%. Urbanization has a negative but insignificant impact on carbon emissions in the low income, middle income and high income panels. Hossain (2011) studied 9 newly industrialized countries (Brazil, China, India, Malaysia, Mexico, Philippines, South Africa, Thailand, and Turkey) over the period 1971 to 2007 and found the existence of a long-run cointegrating vector between $CO_2$ emissions, output, energy consumption, trade openness and urbanization. In the long-run, a 1% increase in: energy use increases $CO_2$ emissions by 1.2%, income increases $CO_2$ emissions by 0.2%, and urbanization lowers $CO_2$ emissions by 0.6%.

In summary, the existing empirical literature is inconclusive on the impact that urbanization has on $CO_2$ emissions. The magnitude and sign of this effect depends upon the data set and estimation technique.

## 3. Empirical model

Following other authors, a Stochastic Impacts by Regression on Population, Affluence and Technology (STIRPAT) model is used to investigate the relationship between urbanization and CO2 emissions (eg. Liddle and Lung, 2010; Martinez-Zarzoso and Maruotti, 2011; Poumanyvong and Kaneko, 2010). The STIRPAT model is based on the Influence, Population, Affluence, and Technology (IPAT) model developed by Ehrlich and Holdren (1971). The IPAT model relates environmental impact to population, affluence (consumption per capita), and technology.

$$I = P \times A \times T \tag{1}$$

The IPAT model has been criticized as 1) being primarily a mathematical equation or an accounting identity which is not suitable for hypothesis testing, and 2) assuming a rigid proportionality between the variables. In response, Dietz and Rosa (1997) proposed a stochastic version of IPAT.

$$I_{it} = a_i P_{it}^b A_{it}^c T_{it}^d e_{it} \tag{2}$$

In Eq. (2), countries are denoted by the subscript i (i = 1,…,N) and the subscript t (t = 1,…,T) denotes the time period. Country specific effects are included through $a_i$ and $\varepsilon_{it}$ represents the random error term. Taking natural logarithms of Eq. (2) provides a convenient linear specification for panel estimation. When all variables are expressed in natural logarithms the estimated coefficients can be interpreted as elasticities.

$$\ln(I_{it}) = b\ln(P_{it}) + c\ln(A_{it}) + d\ln(T_{it}) + \nu_i + \varepsilon_{it} \tag{3}$$

Country specific effects are included through $\nu_i$ and $\varepsilon_{it}$ represents the random error term. The STIRPAT model can easily accommodate additional explanatory variables and in this paper, model (3) is augmented with urbanization (U). The augmented model is

$$\ln(I_{it}) = b\ln(P_{it}) + c\ln(A_{it}) + d\ln(T_{it}) + f\ln(U_{it}) + \nu_i + \varepsilon_{it} \tag{4}$$

When it comes to estimating Eq. (4), a distinction can be made between models with homogeneous slope coefficients and models with heterogeneous slope coefficients. If the assumption of homogeneous slope coefficients is made then these models can be estimated using standard panel regression techniques like pooled OLS (POLS) and various fixed effects (FE), random effects (RE), or GMM specifications. Models with heterogeneous slope coefficients can be estimated using mean group (MG) estimators (eg. Pesaran and Smith, 1995; Pesaran, 1997) or variants on mean group estimators. Estimating panel models with heterogeneous slope coefficients is currently an active area of econometrics (eg. Coakley et al. 2006; Eberhardt and Teal, 2011; Eberhardt et. al., 2013).

Eq. (4) can be transformed into a dynamic model by adding lags of the dependent and each independent variable to the right-hand side of Eq. (4). This formulation is known as an autoregressive distributed lag (ARDL) model. Model selection criteria like SIC can be used to determine the appropriate lag lengths. Dynamic models are advantageous over static models because dynamic models facilitate the calculation of both short-run and long-run elasticities.

Models are estimated using the mean group (MG) estimator of Pesaran and Smith (1995), Pesaran's (2006) Common Correlated Effects Mean Group (CCEMG) estimator, and the Augmented Mean Group (AMG) estimator (Bond and Eberhardt, 2009; Eberhardt and Teal, 2010). The mean group (MG) approach incorporates heterogeneity across countries by allowing all slope coefficients and error variances to vary across panels (or countries as is the case in this paper) (Pesaran and Smith, 1995). The MG approach applies OLS to each panel/country to obtain panel specific slope coefficients and then averages the panel specific coefficients. For large T and N the MG estimator is consistent.

**Table 1**
Average annual growth rates in percent (1971–2009).

| Country | CO2 | Affluence | Population | Urban | intensity |
|---|---|---|---|---|---|
| Brazil | 3.500 | 2.047 | 1.796 | 1.045 | −0.407 |
| Chile | 2.552 | 2.615 | 1.470 | 0.422 | −0.755 |
| China | 5.894 | 7.420 | 1.248 | 2.596 | −4.110 |
| Colombia | 2.357 | 1.918 | 1.958 | 0.795 | −1.721 |
| Egypt, Arab Rep. | 5.895 | 3.247 | 1.918 | 0.066 | 0.622 |
| Hungary | −0.932 | 2.142 | −0.079 | 0.333 | −1.219 |
| India | 5.941 | 3.189 | 1.955 | 1.121 | −1.389 |
| Indonesia | 6.499 | 3.860 | 1.880 | 2.710 | −1.150 |
| Korea, Rep. | 5.765 | 5.230 | 1.108 | 1.815 | 0.554 |
| Malaysia | 6.689 | 3.756 | 2.398 | 1.934 | 0.251 |
| Mexico | 3.497 | 1.293 | 2.018 | 0.699 | 0.388 |
| Morocco | 4.874 | 2.249 | 1.732 | 1.259 | 0.864 |
| Philippines | 2.609 | 1.214 | 2.417 | 0.990 | −1.188 |
| South Africa | 3.086 | 0.449 | 2.060 | 0.628 | 0.576 |
| Thailand | 7.364 | 4.147 | 1.503 | 1.206 | −0.254 |
| Turkey | 4.806 | 2.154 | 1.839 | 1.542 | 0.313 |
| Total | 4.400 | 2.933 | 1.701 | 1.197 | −0.539 |

For inference on the long-run parameters, Pesaran (1997) and Pesaran and Shin (1999) show that including the appropriate number of lags in the order of the ARDL model can simultaneously correct for the problem of residual serial correlation and endogenous regressors. The MG estimator does not, however, incorporate any information on common factors that may be present in the panel data set. Pesaran's (2006) Common Correlated Effects Mean Group (CCEMG) estimator includes cross-sectional dependence and heterogeneous slope coefficients. The cross-sectional dependence is modeled using cross-sectional averages of the dependent and independent variables. These cross-sectional averages account for the unobserved common factors. The unobservable common factors may be nonlinear or non-stationary. The slope coefficients are averaged across panel members. The CCEMG estimators are very robust to structural breaks, lack of cointegration and certain serial correlation (Kapetanios et al., 2011). The Augmented Mean Group (AMG) estimator is an alternative to the Pesaran (2006) CCEMG estimator (Bond and Eberhardt, 2009; Eberhardt and Teal, 2010). In the CCEMG approach the set of unobservable common factors is treated as a nuisance. In the AMG approach the set of unobservable common factors are treated as a common dynamic processes that, depending upon the context, may have useful interpretations.

## 4. Data

The data set is an unbalanced panel of 16 emerging countries followed over the years 1971–2009. The countries are selected from the MSCI classification of emerging markets.[2] MSCI classifies countries as emerging if their financial markets meet certain size, liquidity, and market accessibility criteria.[3] The list of countries includes: Brazil, Chile, China, Colombia, Egypt, Hungary, India, Indonesia, Korea (South), Malaysia, Mexico, Morocco, Philippines, South Africa, Thailand, and Turkey.[4]

In the empirical analysis, CO2 is the natural logarithm of $CO_2$ emissions (metric tons of carbon dioxide emissions), Affluence is the natural log of real per capita GDP (GDP per capita, in constant 2005 US dollars), Population is the natural log of total population, and Urban is the natural log of urbanization (measured by the fraction of the population living in urban areas). Following Liddle and Lung (2010), Poumanyvong and Kaneko (2010), and Martinez-Zarzoso and Maruotti (2011) the technology variable in Eq. (4) is measured using energy intensity. Intensity is the natural log of total energy use per dollar of GDP (energy use in kg of oil equivalent relative to GDP, constant 2005 US dollars). The data

[2] http://www.msci.com/products/indices/tools/index_country_membership/emerging_markets.html

[3] http://www.msci.com/products/indices/market_classification.html

[4] MSCI lists 21 countries as emerging. Due to data limitations, Czech Republic, Peru, Poland, Russia, and Taiwan were omitted from the analysis.

**Table 2**
Correlations.

| | CO2 | Affluence | Population | Urban | Intensity |
|---|---|---|---|---|---|
| CO2 | 1.000 | | | | |
| Affluence | −0.066 | 1.000 | | | |
| Population | 0.791 | −0.575 | 1.000 | | |
| Urban | −0.194 | 0.863 | −0.557 | 1.000 | |
| Intensity | 0.485 | −0.737 | 0.626 | −0.774 | 1.000 |

(obs = 624)

**Table 3**
Tests for cross-section dependence.

| Variable | CD-test | p-value | corr | abs(corr) |
|---|---|---|---|---|
| CO2 | 49.49 | <0.001 | 0.723 | 0.912 |
| Affluence | 54.78 | <0.001 | 0.801 | 0.804 |
| Population | 53 | <0.001 | 0.775 | 0.969 |
| Urban | 54.63 | <0.001 | 0.799 | 0.873 |
| Intensity | 0.12 | 0.904 | 0.002 | 0.484 |

are obtained from the World Bank (2013) World Development Indicators online data base. [5]

Average annual growth rates for the variables are shown in Table 1. The average annual growth rate in $CO_2$ emissions ranges from a high of 7.36% in Thailand to a low of −0.93% in Hungary. Thailand, Malaysia, and Indonesia each have average annual growth rates in $CO_2$ emissions greater than 6%. The average annual growth rate in affluence (per capita GDP) ranges from a high of 7.42% (China) to low of 0.45% (South Africa). China, Korea, and Thailand each experienced average annual growth rates in affluence greater that 4%. On average, the fastest growth in population occurred in the Philippines, Malaysia, South Africa, and Mexico. Each of these countries has average annual growth rates in population greater than 2%. Hungary actually experienced a negative average annual growth rate in population. Indonesia and China each recorded average annual increases in urbanization greater than 2%. Egypt had the lowest average annual growth rate in urbanization (0.67%). Average annual growth rates in energy intensity were the highest in Morocco, Egypt, South Africa and Korea (each larger than 0.50%). Negative average annual growth rates in energy intensity were recorded for about half of the countries with China having the lowest average annual growth rate in energy intensity (−4.11%).

Correlations are presented in Table 2. CO2 emissions correlate negatively with affluence and urbanization. CO2 emissions correlate positively with population and energy intensity.

Prior to formal econometric modeling, it is important to have an understanding of the time series properties of the data. Unit root tests that assume cross-sectional independence can have low power if estimated on data that have cross-sectional dependence. Pesaran's (2004) cross-section dependence (CD) test was used to check for cross-sectional independence. The CD tests indicate that, except for energy intensity, each series exhibits cross-sectional dependence (Table 3).

As a first investigation into unit roots, the Im et al. (2003) (IPS) panel unit root test was run for each series (Table 4). These tests were run with a constant and trend term and an automatic lag selection process using the AIC with a maximum of five lags. These tests clearly indicate that four of the series are first difference stationary and urban is stationary in levels. However, as indicated from Table 3, four out of five variables exhibit cross-sectional variation. As a result, Pesaran's (2007) CIPS (Z(t-bar)) test for unit roots was calculated. This is a unit root test that allows for cross-sectional dependence. All tests were estimated with a constant term and trend. The CIPS tests indicate that, except for urbanization, each series contains a unit root. These results are similar to Liddle (2013) who also found urbanization is stationary in levels. The mixture of I(0) and I(1) variables indicates that standard panel regression techniques won't be applicable in this case. Consequently, modeling is carried out using recently developed techniques for heterogeneous panels that are robust to cointegration and cross-sectional dependence (Chudik et al., 2011; Kapetanios et al., 2011; Pesaran and Tosetti, 2011).

[5] Urbanization refers to The World Bank's definition of the percentage of the population living in urban areas as defined by national statistical offices (http://data.worldbank.org/indicator/SP.URB.TOTL.IN.ZS). However, urban areas can be defined differently by different national statistical offices and in general there is no universally accepted definition of urbanization (eg. Vlahov and Galea, 2002). Moreover, a country's definition of an urban area can change across time.

## 5. Empirical results

The empirical analysis is conducted by estimating a series of regression models under different assumptions about slope coefficients and dynamics. The first suite of results is for static models with homogeneous slope coefficients. Empirical results are presented for specifications estimated using pooled OLS with panel corrected standard errors (PCSE), fixed effects (FE), and random effects (RE) (Table 5). The estimated coefficient on the affluence variable is between 1.091 and 1.143 and is statistically significant. The estimated coefficient on the population variable ranges between 0.956 and 1.884 and is statistically significant. The estimated coefficient on the urbanization variable under fixed effects or random effects is within the range of values reported by other authors (eg. Cole and Neumayer, 2004; Martinez-Zarzoso and Maruotti, 2011; Parikh and Shukla, 1995; Poumanyvong and Kaneko, 2010). The estimated coefficient on the energy intensity variable is positive and statistically significant. The results in Table 5 indicate that increases in affluence, population or energy intensity increase $CO_2$ emissions. An increase in urbanization can have either positive or negative impacts on $CO_2$ emissions, depending upon the estimation technique. The residuals are tested for cross-sectional dependence using Pesaran's (2004) CD test and stationarity is tested using Pesaran's (2007) CIPS. It is important to test for stationarity in the residuals because residual stationarity is an important part of a good fitting econometric model. Applying the CD test to the regression residuals provides strong evidence of cross-section dependence in each specification. More troubling is the CIPS test indicates that all regressions have non-stationary residuals which indicate a poorly fitting model.

Table 6 presents empirical results for static models with heterogeneous slope coefficients. The estimated coefficient on the affluence variable is between 1.032 and 1.158 and statistically significant at the 1% level. The estimated coefficient on the population variable is between 1.789 and 3.529 and significant at the 5% level. The estimated coefficient on the energy intensity variable is between 0.830 and 0.978 and statistically significant at the 1% level. The estimated coefficient on the urban variable is negative but statistically insignificant in two specifications and positive and significant in one specification. The CD test indicates some evidence of cross section dependence in the CCEMG and AMG specifications but no statistically significant evidence of cross section dependence in the MG specification. All three specifications have stationary residuals which may be the result of controlling for heterogeneous parameters and cross section dependence. Notice that the RMSE values reported in Table 6 are one order of magnitude smaller than those reported in Table 5 indicating a preference for models estimated with heterogeneous slope coefficients.

**Table 4**
Tests for unit roots.

| Variable | IPS | IPS 1ST DIFF | CIPS | CIPS 1ST DIFF |
|---|---|---|---|---|
| CO2 | −0.367 | −17.315[a] | 0.598 | −2.999[a] |
| Affluence | −0.099 | −8.896[a] | 1.474 | −3.372[a] |
| Population | 4.015 | −4.413[a] | −5.341 | −1.561[c] |
| Urban | −2.389[a] | 2.631 | −1.675[b] | 4.474 |
| Intensity | −0.657 | −17.337[a] | 2.111 | −4.724[a] |

The superscripts a, b and c denote significance at the 1%, 5% and 10% levels respectively.

**Table 5**
Pooled estimates (static).

| | PCSE | FE | RE |
|---|---|---|---|
| Affluence | 1.111[a] | 1.143[a] | 1.091[a] |
| | (109.56) | (7.45) | (6.67) |
| Population | 0.956[a] | 1.884[a] | 1.322[a] |
| | (120.78) | (8.27) | (10.57) |
| Urban | −0.0924[b] | 0.0555 | 0.219 |
| | (−2.13) | (0.21) | (0.95) |
| Intensity | 1.094[a] | 0.814[a] | 0.865[a] |
| | (73.11) | (4.85) | (4.90) |
| Constant | −12.55[a] | −30.61[a] | −20.56[a] |
| | (−108.18) | (−8.54) | (−8.08) |
| RMSE | 0.247 | 0.112 | 0.122 |
| Observations | 624 | 624 | 624 |
| Groups | 16 | 16 | 16 |
| CD | −2.41 [b] | −3.89 [a] | −3.99 [a] |
| CIPS | 1.28 | 0.01 | 0.15 |

*t* statistics in parentheses.
Estimation is from an unbalanced panel of 16 emerging economies covering the period 1971–2009.
Time dummy variables included in FE and RE specifications.
Robust t statistics reported.
[a] $p < 0.01$.
[b] $p < 0.05$.

**Table 6**
Heterogeneous estimates (static).

| | MG | CCEMG | AMG |
|---|---|---|---|
| Affluence | 1.133[a] | 1.158[a] | 1.032[a] |
| | (12.95) | (15.29) | (13.29) |
| Population | 1.789[a] | 3.529[b] | 2.410[a] |
| | (2.80) | (2.03) | (3.97) |
| Urban | −0.0855 | 1.286[c] | −0.00328 |
| | (−0.15) | (1.76) | (−0.01) |
| Intensity | 0.978[a] | 0.830[a] | 0.907[a] |
| | (5.83) | (8.22) | (6.10) |
| Constant | −27.41[a] | −20.63 | −38.35[a] |
| | (−3.10) | (−1.10) | (−4.21) |
| RMSE | 0.0488 | 0.0303 | 0.0418 |
| Observations | 624 | 624 | 624 |
| Groups | 16 | 16 | 16 |
| CD | 0.60 | −2.09 [b] | −1.88 [c] |
| CIPS | −4.36 [a] | −10.59 [a] | −5.29 [a] |

*t* statistics in parentheses.
Estimation is from an unbalanced panel of 16 emerging economies covering the period 1971–2009. Estimated coefficients are un-weighted averages across countries.
[a] $p < 0.01$.
[b] $p < 0.05$.
[c] $p < 0.10$.

Heterogeneous parameter estimates from the dynamic panel model are reported in Table 7.[6] Looking first at the contemporaneous variables, the estimated coefficient on the affluence variable is positive and statistically significant at the 1% level. The values range between 1.041 and 1.128 indicating little variation between the three estimation methods. The estimated coefficient on the population variable ranges between 0.742 and 2.165 and is statistically significant at the 1% level in two of the specifications. The estimated coefficient on the urban variable is positive but not statistically significant. Notice that the estimated coefficients on the urban variable from the heterogeneous dynamic specifications are larger than those found from the static specifications (Tables 5 and 6) and similar to the values reported by other authors (eg. Martinez-Zarzoso and Maruotti, 2011; Poumanyvong and Kaneko, 2010). The estimated coefficient on the energy intensity variable is positive and statistically significant at the 1% level. The estimated coefficient on lagged $CO_2$ emissions is positive and statistically significant at the 10% level and ranges between 0.101 and 0.471 indicating a low to moderate degree of persistence. The estimated coefficient on the lagged affluence variable is negative and statistically significant at the 1% level in two of the specifications. The estimated coefficient on the lagged intensity variable is negative and statistically significant at the 5% level in two of the specifications. The CD test indicates no evidence of cross section dependence at the 1% level. There is no evidence of nonstationary residuals in any of the specifications at conventional levels of significance. The dynamic specification with heterogeneous slope coefficients is preferred over static specifications with homogeneous slope coefficients because of the lower root mean square error (RMSE) values and stationary residuals.

Since the estimated coefficient on the urbanization variable is statistically insignificant, the dynamic models were re-estimated omitting the urbanization variable. The estimated coefficients indicate that lagged CO2 emissions has a positive and statistically significant impact on current period CO2 emissions while, current period affluence and intensity each have positive and statistically significant impacts on CO2 emissions (Table 8). The estimated coefficient on the population variable is positive in each specification and statistically significant in two specifications. The residual diagnostic tests indicate stationary residuals and no evidence of cross section dependence at the 1% level of significance. Notice however, that for each specification, the estimation with the urbanization variable (Table 7) produces slightly lower root mean square error (RMSE) values (4% smaller in the case of MG, 11% smaller in the case of CCEMG, and 5% smaller in the case of AMG) than estimation without the urbanization variable (Table 8). The differences in RMSE values are not too great and in the interest of parsimony, the parameter estimates from Table 8 are preferred.

## 6. Implications

The empirical results reported in Table 8 can be used to calculate short-run and long-run $CO_2$ elasticities (Table 9). The short-run affluence elasticities range from 1.125 to 1.193 while the long-run affluence elasticities range from 0.904 to 0.996. For each specification, the short-run affluence elasticity is slightly larger than the corresponding long-run elasticity.

**Table 7**
Heterogeneous estimates (dynamic).

| | MG | CCEMG | AMG |
|---|---|---|---|
| CO2(−1) | 0.471[a] | 0.101[c] | 0.376[a] |
| | (6.47) | (1.83) | (5.52) |
| Affluence | 1.128[a] | 1.041[a] | 1.091[a] |
| | (13.89) | (12.83) | (15.33) |
| Affluence(−1) | −0.575[a] | −0.134 | −0.490[a] |
| | (−3.79) | (−0.99) | (−3.52) |
| Population | 0.742[c] | 2.165 | 1.318[b] |
| | (1.87) | (0.98) | (2.55) |
| Urban | 0.495 | 1.518 | 0.536 |
| | (1.26) | (1.42) | (1.18) |
| Intensity | 0.794[a] | 0.781[a] | 0.772[a] |
| | (8.22) | (7.74) | (7.46) |
| Intensity(−1) | −0.347[a] | −0.105 | −0.290[b] |
| | (−2.91) | (−1.01) | (−2.49) |
| Constant | −12.27[b] | −33.71 | −22.04[a] |
| | (−2.24) | (−1.53) | (−2.95) |
| RMSE | 0.0351 | 0.0257 | 0.0329 |
| Observations | 608 | 608 | 608 |
| Groups | 16 | 16 | 16 |
| CD | 1.27 | −2.40[b] | −0.65 |
| CIPS | −7.91[a] | −12.47[a] | −8.48[a] |

*t* statistics in parentheses.
Estimation is from an unbalanced panel of 16 emerging economies covering the period 1971–2009. Estimated coefficients are un-weighted averages across countries.
[a] $p < 0.01$.
[b] $p < 0.05$.
[c] $p < 0.10$.

[6] This model is selected using the SIC from a maximum of one lag on each right-hand-side variable.

**Table 8**
Heterogeneous estimates (dynamic) without urbanization variable.

| | MG | CCEMG | AMG |
|---|---|---|---|
| CO2(−1) | 0.556[a] | 0.314[a] | 0.470[a] |
| | (9.88) | (6.13) | (8.46) |
| Affluence | 1.193[a] | 1.125[a] | 1.145[a] |
| | (15.33) | (12.72) | (16.07) |
| Affluence(−1) | −0.766[a] | −0.442[a] | −0.666[a] |
| | (−5.98) | (−3.90) | (−5.78) |
| Population | 0.776[b] | 1.963 | 1.333[a] |
| | (2.38) | (1.19) | (3.66) |
| Intensity | 0.856[a] | 0.843[a] | 0.819[a] |
| | (9.59) | (8.22) | (8.33) |
| Intensity(−1) | −0.485[a] | −0.207[c] | −0.399[a] |
| | (−5.46) | (−1.76) | (−4.79) |
| Constant | −11.16[b] | −11.56 | −20.40[a] |
| | (−2.26) | (−1.50) | (−3.56) |
| RMSE | 0.0365 | 0.0290 | 0.0345 |
| Observations | 608 | 608 | 608 |
| Groups | 16 | 16 | 16 |
| CD | 1.47 | −2.00[b] | −0.14 |
| CIPS | −6.40[a] | −10.24[a] | −6.87[a] |

*t* statistics in parentheses.
Estimation is from an unbalanced panel of 16 emerging economies covering the period 1971–2009. Estimated coefficients are un-weighted averages across countries.
[a] $p < 0.01$.
[b] $p < 0.05$.
[c] $p < 0.10$.

**Table 9**
$CO_2$ emissions elasticities.

| Elasticities | MG | CCEMG | AMG |
|---|---|---|---|
| short-run | | | |
| Affluence | 1.193 | 1.125 | 1.145 |
| Population | 0.776 | 1.963 | 1.333 |
| Intensity | 0.856 | 0.843 | 0.819 |
| long-run | | | |
| Affluence | 0.962 | 0.996 | 0.904 |
| Population | 1.748 | 2.862 | 2.515 |
| Intensity | 0.836 | 0.927 | 0.792 |

Elasticities derived from parameter estimates in Table 8.

The short-run population elasticities range between 0.776 and 1.963. The long-run elasticities range between 1.748 and 2.862. For each specification, the long-run population elasticities are larger than the short-run population elasticities. The short-run energy intensity elasticities are in the range 0.819 to 0.856 and these values are very similar to the long-run elasticities. All of these short-run and long-run elasticities are positive indicating that increases in affluence, population, or energy intensity increase $CO_2$ emissions in both the short-run and the long-run.

These results have serious implications for the buildup (stock) of $CO_2$ in the atmosphere. $CO_2$ emitted into the atmosphere lasts for a long time and today's emissions (a flow) contribute to the total stock of $CO_2$ in the atmosphere.[7] Since affluence and population are likely to continue increasing in emerging economies, this leaves reductions in energy intensity as the only practical way to reduce $CO_2$ emissions.

Since urbanization is found to have no statistically significant impact on CO2 emissions at conventional levels, omitting urbanization from the types of econometric models estimated in this paper will not have much impact on forecasts of carbon dioxide emissions. Energy and environmental polices formulated without considering the impacts of urbanization on carbon dioxide emissions will probably meet their stated objectives.

## 7. Conclusions

This paper uses a STIRPAT model to explore the impact that urbanization has on carbon dioxide emissions in emerging economies. It is expected that urbanization will continue rising in emerging economies and understanding how urbanization affects $CO_2$ emissions is an important and timely topic to study. A better understanding of how urbanization affects $CO_2$ emissions is necessary from a sustainable development perspective.

This study uses recently developed heterogeneous panel regression techniques like mean group estimators and common correlated effects estimators to model the impact that energy use, income, and urbanization has on $CO_2$ emissions for a panel of emerging economies. In particular, models are estimated using the mean group (MG) estimator of Pesaran and Smith (1995), Pesaran's (2006) Common Correlated Effects Mean Group (CCEMG) estimator, and the Augmented Mean Group (AMG) estimator of Eberhardt and Teal (2010) and Bond and Eberhardt (2009). In addition, results are presented for static and dynamic specifications.

The estimated contemporaneous coefficient on the affluence variable is fairly similar across different estimation techniques. This is also the case for the energy intensity variable. These results are important in establishing how remarkably robust the estimated coefficients on affluence and energy intensity are to different estimation techniques (homogenous slope coefficients or heterogeneous slope coefficients) and assumptions about the dynamics (static or dynamic) even in cases where formal diagnostic tests reveal evidence of miss-specification.

The estimated contemporaneous coefficient on the urbanization variable is, however, sensitive to the estimation technique. For static specifications estimated with homogeneous slope coefficients, the estimated coefficient on the urbanization variable is negative and statistically significant in one of the specifications and positive and statistically insignificant in two of the specifications. For the fixed effects and random effects specifications, the estimated coefficient on the urbanization variable is within the range of values found by other authors. Residual diagnostic tests indicate that static specifications with homogeneous slopes are, however, miss-specified.

For static specifications estimated with heterogeneous slope coefficients, the estimated coefficient on the urbanization variable is positive and statistically significant in one of the specifications and negative but statistically insignificant in two of the specifications. For dynamic specifications estimated with heterogeneous slope coefficients, the estimated coefficient on the urbanization variable is statistically insignificant at the 10% level indicating that the urbanization variable can be dropped from the model. Based on residual diagnostic tests, the dynamic model with heterogeneous slope coefficients is preferred.

One of the implications of these results is that omitting the urbanization variable will have little impact on emissions reduction strategies or sustainable development policies. The theories of ecological modernization and urban environmental transition recognize that urbanization can have both positive and negative impacts on the natural environment with the net effect being hard to determine a priori. Higher urbanization is associated with higher economic activity. Higher economic activity generates higher wealth and wealthier residents often demand more energy intensive products (eg. automobiles, air conditioning, etc.) which can increase carbon dioxide emissions. Wealthier residents are also likely to care more about the environment. Increased urbanization also helps to facilitate economies of scale for public infrastructure and these economies of scale lead to lower environmental damages. The results of this paper indicate that the two opposing effects of urbanization on $CO_2$ emissions tend to cancel each other out leaving the net impact of urbanization on $CO_2$ emissions statistically insignificant from zero.

[7] It is estimated that between 65% and 80% of $CO_2$ released into the atmosphere dissolves into the oceans over a period of between 20 to 200 years. The remaining $CO_2$ dissolves through various weathering processes and this can take several thousands of years (http://www.guardian.co.uk/environment/2012/jan/16/greenhouse-gases-remain-air).

Estimates from the dynamic model with heterogeneous slope coefficients indicate that long-run population elasticities (between 1.748 and 2.862) are greater than long-run affluence elasticities (between 0.904 and 0.996) and long-run affluence elasticities are greater than long-run energy intensity elasticities (between 0.792 and 0.927). All of these long-run elasticities are positive indicating that increases in affluence, population, or energy intensity increase $CO_2$ emissions in the long-run.

The results of this paper show that the most direct way for emerging economies to reduce $CO_2$ emissions is to reduce affluence, population, and energy intensity. Emerging economies are, however, currently on a trajectory of increasing affluence and population. Consequently, a reduction in $CO_2$ emissions is going to have to come from an increase in energy efficiency and a greater effort at fuel switching from fossil fuels to renewables. Pricing of carbon dioxide emissions either through taxes or a cap and trade system would also be beneficial in helping to reduce the consumption of fossil fuels.

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