Journal of Urban Economics 67 (2010) 404–418

Contents lists available at ScienceDirect

Journal of Urban Economics

www.elsevier.com/locate/jue

The greenness of cities: Carbon dioxide emissions and urban development

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ARTICLE INFO

Article history:
Received 12 December 2008
Revised 20 November 2009
Available online 16 December 2009

JEL classification:
Q4
R2
R3

Keywords:
Greenhouse gases
Cities
Urban growth
Transportation
Electricity consumption
Regulation

ABSTRACT

Carbon dioxide emissions may create significant social harm because of global warming, yet American urban development tends to be in low density areas with very hot summers. In this paper, we attempt to quantify the carbon dioxide emissions associated with new construction in different locations across the country. We look at emissions from driving, public transit, home heating, and household electricity usage. We find that the lowest emissions areas are generally in California and that the highest emissions areas are in Texas and Oklahoma. There is a strong negative association between emissions and land use regulations. By restricting new development, the cleanest areas of the country would seem to be pushing new development towards places with higher emissions. Cities generally have significantly lower emissions than suburban areas, and the city-suburb gap is particularly large in older areas, like New York.

1. Introduction

While there remains considerable debate about the expected costs of global warming, a growing scientific consensus believes that greenhouse gas emissions create significant risks of climate change. A wide range of experts have advocated reducing individual carbon footprints and investing billions to reduce the risks of a major change in the earth's environment (Stern, 2008).[1] Almost 40% of total US carbon dioxide emissions are associated with residences and cars, so changing patterns of urban development and transportation can significantly impact emissions.[2] How do major cities differ with respect to their per-household emissions levels?

In Section 2 of this paper, we review the basic theory of spatial environmental externalities. If emissions are taxed appropriately, then private individuals will make appropriate decisions about location choices without any additional location-specific policies. When emissions are not taxed, then location decisions will be inefficient. The optimal location-specific tax on building in one place versus another equals the difference in emissions times the gap between the social cost of emissions and the current tax on these emissions. Even if there was an appropriate carbon tax, location decisions might still be sub-optimal if governments subsidize development in high emissions areas or artificially restrict development in low emissions areas.

In Section 3 of this paper, we measure household carbon dioxide emissions production in 66 major metropolitan areas within the United States.[3] For a standardized household, we predict this household's residential emissions and emissions from transportation use. We look at emissions associated with gasoline consumption, public transportation, home heating (fuel oil and natural gas) and electricity usage. We use data from the 2001 National Household Travel Survey to measure gasoline consumption. We use year 2000 household level data from the Census of Population and Housing to measure household electricity, natural gas and fuel oil consumption. To aggregate gasoline, fuel oil and natural gas into a single carbon dioxide emissions index, we use conversion factors. To determine the carbon dioxide impact of electricity consumption in different major cities, we use regional average power plant emissions factors, which reflect the fact that some regions' power is gen-

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[1] See also the critical reviews in Weitzman (2007) and Nordhaus (2007).

[2] See http://www.eia.doe.gov/oiaf/1605/ggrpt/carbon.html for sources of carbon dioxide emissions.

[3] Our work parallels the findings of the Vulcan Project at Purdue University (http://www.purdue.edu/eas/carbon/vulcan/index.php), Brown and Logan (2008), and the recent Brookings Institution study by Brown et al. (2008). In contrast to these studies, we document spatial differences in the carbon footprint for a standardized household. From the perspective of urban economics, we believe that this is the right thought experiment for measuring the marginal social cost of urban growth in different cities.

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doi:10.1016/j.jue.2009.11.006

erated by dirtier fuels such as coal while other regions rely more on renewable energy sources. We distinguish between the emissions of an area's average house and the emissions of a marginal house by looking particularly at homes built in the last 20 years.

Our estimates suggest a range of carbon dioxide emissions from about 19 tons per household per year in San Diego and Los Angeles to about 32 tons in Oklahoma City and Memphis. The older cities of the Northeast tend to lie within those extremes. While people in these older cities drive less, they need large amounts of heating and produce more emissions as a result. For illustrative purposes, we use a social cost figure of 43 dollars per ton of carbon dioxide, which implies that the social cost of a new home in Houston is $550 dollars more per year than the social cost of a new home in San Francisco. We recognize that this spatial externality gap narrows if one chooses to use a smaller social cost figure. Today, environmental economists are debating what might be a socially optimal time path for carbon taxes to follow. Our imprecise figure lies on the time path proposed by Metcalf (2007).

We also use our methodology to compare the emissions in central cities and suburbs for 48 major metropolitan areas. In general, central city residence is associated with lower levels of emissions, although there are a few places where that fact is reversed. Carbon dioxide emissions differences within metropolitan areas are smaller than the differences across metropolitan areas. The place with the most extreme emissions difference between central cities and suburbs is New York, where we estimate that suburban development causes more than 300 dollars more damage in carbon dioxide emissions than central city development.

Across metropolitan areas, we find a weak positive connection between the level of emissions and recent growth when we weight by initial population size. We find a strong negative correlation between emissions and the level of land use controls. Overall, the metro areas with the lowest per-household carbon dioxide emissions levels are also the most restrictive towards new development. The observed negative correlation between land use controls and population may be spurious, if these regulations are reflecting other more exogenous factors, like a lack of buildable land (as in Saiz, forthcoming). Moreover, it is conceivable, although we believe unlikely, that even if land use controls do limit new development in regulated places, they do not push development from more to less regulated places. But if developers respond to land use controls by building less in more regulated places and more in places that have less limitations on building, then the negative correlation between land-use restrictions and carbon emissions suggests that current restrictions may be doing exactly the opposite of what a climate change activist may have hoped. More empirical work is needed to investigate whether those restrictions, often implemented for local environmental reasons (such as to preserve open space or reduce neighborhood traffic), are actually pushing new development towards the least environmentally friendly urban areas (Fischel, 1999; Glaeser and Tobio, 2008). We now turn to the basic economics of environmental externalities and urban development.

2. Urban development and environmental externalities

Why is it useful to know the carbon dioxide emissions associated with different locations throughout the US? In an earlier draft of this paper (Glaeser and Kahn, 2008), we presented a simple model that makes two major points. First, if emissions are actually taxed at the appropriate rates then there is no global warming-related reason for government policy to favor one place over another and no policy-related reason to care about emissions in different places. Glaeser (2009) notes that this result also relies on an implicit assumption that there are no other public policies, like the home mortgage interest deduction or subsidized highway construction, that could distort energy consumption decisions.

Our second point was that these conditions are unlikely to hold in the real world, and as a result there is an environmental externality associated with moving into different locales. The size of the externality associated with moving into place A rather than place B equals the expected emissions in A minus the expected emissions in B times the social cost of carbon emissions minus the current carbon tax. This result motivates our empirical strategy of estimating the carbon emissions for a typical family in different geographic settings throughout the US and multiplying those emissions by an estimate of the social cost of carbon dioxide emissions. If the carbon tax was currently zero, then our figures would represent the second best optimal location tax.

We are not, in fact, in any sense advocating such a tax, which is in many ways less efficient than a direct tax on energy usage. However, we do think that it is useful to ask whether current government policies are pushing people towards areas that have lower average emissions or higher average emissions. For example, a growing literature has documented a strong connection between land use regulations and population growth at the local and metropolitan area level. For example, Glaeser and Ward (2009) show that population growth is significantly lower in those Boston-area cities that restrict building more assiduously. Moreover, new construction falls in cities after they impose more stringent controls. Across metropolitan areas, there is a strong negative correlation between the strictness of land use regulation and the amount of building activity (Glaeser and Gyourko, 2008). This correlation does not necessarily imply causality, but it does seem quite plausible that legally restricting the number of buildings per acre or imposing impact fees or lengthy construction delays, in high demand areas, does, in fact, limit the amount of building on an acre of land.

In an earlier draft of this paper (Glaeser and Kahn, 2008), we presented a simple model where land use controls increased the cost of building, illustrated that if zoning is more restrictive in those areas that have particularly low energy use, then these land use regulations will increase carbon emissions. If the areas that restrict land use most severely are also places that have high carbon emissions, then this land use controls will reduce greenhouse gases. In this paper, we examine whether places that restrict housing development have particularly high or low carbon emissions.

Throughout this paper, we focus exclusively on greenhouse gas emissions as the primary indicator of the environmental externality. In previous research (Glaeser, 1998; Kahn, 2006), we have investigated the ambient air pollution costs of city growth. Given ongoing ambient air pollution progress and the growing concern about the production of greenhouse gas emissions, we believe that it is important to focus on this relatively understudied environmental indicator.

3. Greenhouse gas emissions across metropolitan areas

We now turn to estimating the quantity of carbon dioxide emissions that households produce in 66 major metropolitan areas.[4] Our goal is to calculate the marginal impact of an extra household in location *j* on the total carbon dioxide emissions of that location. The marginal household and the average household need not be the same, and we will try to create marginal estimates by comparing the emissions of an average household and the emissions produced by households who live in newer housing. Ideally, we would also be

[4] Our sample includes 66 metropolitan areas with at least 250,000 households based on year 2000 Census IPUMS. In the year 2000, 72% of all metropolitan area residents live in one of these 66 metropolitan areas. We use the IPUMS definitions of metropolitan areas to assign households to metropolitan areas. Table two lists the set of metropolitan areas that we study.

able to address the possibility that marginal emissions associated with more electricity generation are different from the average emissions, but we have no way of doing this well. In principle, the marginal resident could foster the development of a new lower polluting electric power plant, or the marginal megawatt of electricity could involve more harmful energy uses.[5]

We consider four main sources of carbon dioxide emissions: private within-city transport, public transportation, residential heating (natural gas and fuel oil) and residential electricity consumption. Car usage and home heating involves a relatively simple translation from energy use to carbon dioxide emissions. Household electricity use and public rail transit requires us to convert megawatt hours of usage into carbon dioxide emissions by using information about the carbon dioxide emissions associated with electricity production in different regions of the country. We are not considering the impact of shifting people on the energy emissions associated with moving goods and we are not considering the impact of shifting people on industrial output. The problem of figuring out how industrial location and the transport network changes with different urban development patterns is beyond the scope of this paper.[6]

One natural concern with our approach is that households in areas that spend more on energy have less income to spend on other things that also involve greenhouse gas emissions. If people in Texas are spending a lot on air conditioning and gas at the pump, then perhaps they are spending less on consumption goods that are equally environmentally harmful. We cannot fully address this concern, since it would require a complete energy accounting for every form of consumption, but we do not believe our omissions fatally compromise our empirical exercise. After all, few forms of consumption involve nearly as much carbon emissions as the direct purchase and use of energy. Moreover, areas that tend to have high levels of energy use are generally low cost areas like far flung suburbs or the Sunbelt, where people have more, not less, money available for other things. One can argue that the high land costs in expensive cities represent a transfer to earlier property owners who use their property-related revenues to buy more energy, but tracing through this chain of money and emissions is far too complicated a task for us.

3.1. Car usage and emissions

We begin with estimating gasoline usage across metropolitan areas. Our primary data source is the 2001 National Household Transportation Survey (NHTS). This data source contains information on household characteristics and reported annual miles driven. The NHTS uses information on the types of vehicles the household owns to estimate annual gasoline consumption.[7] The survey also reports the population density of the household's census tract, and zip code identifiers that enable us to use zip code characteristics to predict gasoline usage. We use these zip code identifiers to calculate each household's distance to the metropolitan area's Central Business District.

We use the NHTS' main sample. For each household, the data set reports each vehicle's gallons of gasoline per year. We sum this up by household over all vehicles listed in the data set. We keep only observations for households who live in metropolitan areas we can identify and drop households who are not part of the national sample (based on their sampling weight). We restrict the sample to households whose head is between the ages of 18 and 65 and for whom we have complete demographic and geographic data.[8] These data rules yield a sample that includes 11,728 observations.

Our primary approach is to use the NHTS to predict gasoline usage based on individual and zip code level characteristics. We regress:

$$\text{Gasoline} = \sum_j \beta_j Z_k^j + \sum_q \gamma_q X_i^q + \mu_k + \varepsilon_i \tag{1}$$

where Z_k^j refers to the value of zip code characteristic j in zip code k, β_j reflects the impact of those variables, X_i^q refers to the value of individual level q for person i, γ_q is the coefficient on that characteristic and the other two terms are individual level and zip code level error terms. Since there are a significant number of truly extraordinary outliers, and since we are running this regression in levels rather than logs, we top code the top 1% of the sample. The results of this equation are shown in Table 1.

The overall R^2 of the equation is 30%. Family size and income strongly increase gas consumption, so it is important to control for these characteristics. The area-level characteristics have the predicted signs. Population density, whether at the tract, zip code or metropolitan area level, reduces gasoline usage (see Golob and Brownstone, 2005). Distance to the metropolitan's central business district is associated with increases in average gasoline consumption.[9] We also interact census tract density with region dummies and find that the density–gas consumption relationship is weaker in the West.

We then take these coefficients and predict gasoline usage for a family with an income of 62,500 dollars and 2.62 members for each census tract located within 66 major metropolitan areas.[10] Intuitively, we are predicting what the average gasoline consumption would be for a standardized household if it lived in each of census tracts within the 66 major metropolitan areas. Specifically, our predicted value for a census tract with characteristics Z_k^j is $\sum_j \beta_j Z_k^j + \sum_q \gamma_q X_{Ave}^q$, where X_{Ave}^q denoted the individual characteristics of a standardized individual. We then form metropolitan area averages by aggregating up from the tract level using the tract's household count as the weight.[11]

These estimates control for household level income and size, but they are, of course, imprecise. We are only using two primary characteristics for each tract, its proximity to downtown and its population density. As such, there will be an almost automatic relationship between urban sprawl and gasoline usage since gasoline usage decreases with density and increases with distance from downtown. There is a less automatic connection between gasoline consumption and metropolitan area population size, which is shown in Fig. 1. On average, a .1 log point increase in MSA population size is associated with a 7.3 gallon reduction in the consumption of gallons of gas.[12]

[5] To the extent that all regions have a similar relationship between marginal and average usage, then the implications of this work for inter city comparisons, may not be terribly effected by our inability to measure true marginal impacts.

[6] Since much of modern industry is capital intensive and has low transport costs, we suspect it might not move that much in response to a population shift. We recognize that population shifts will change the carbon emissions resulting from the shipping of final output from factories to final consumers.

[7] For an analysis of how urban form affects vehicle miles traveled based on the 1990 version of this micro data set Bento et al. (2005).

[8] Below, our standardized household head will be 48 years old.

[9] We recognize that our cross-sectional regressions raise issues of causality. People who self select to live at lower density may do so because they like to drive. In this case, we would over-estimate the role of population density in causing reduced consumption of gasoline.

[10] These demographic statistics are based on the sample means for the 66 metropolitan areas that are listed in Table 2 from the year 2000 Census IPUMS.

[11] We include all census tracts within thirty miles of the metropolitan area's CBD.

[12] An alternative approach is to run regression (1) using metropolitan area fixed effects instead of region fixed effects, and then use those metropolitan area fixed effects as our measure of gasoline usage. We have estimated metropolitan area gasoline usage in this alternative manner, and the correlation between our measure and the measure estimated using metropolitan area fixed effects is high.

Table 1
Gallons of gasoline consumed per year.

	Household's annual total gasoline consumption (gallons)
Midwest	78.998 (0.41)
South dummy	31.799 (0.2)
West dummy	−417.605 (4.32)
Log(zip code distance to CBD)	64.118 (5.28)
Log(census tract density)	−116.851 (17.25)
Log(metropolitan area density)	−38.4 (2.12)
Log(census tract density) * midwest	3.67 (0.17)
Log(census tract density) * south	10.215 (0.53)
Log(census tract density) * west	59.899 (5.37)
Log(household income)	299.264 (16.4)
Household size	163.704 (28.8)
Household head age	3.127 (6.44)
Constant	−1731.832 (6.92)
Observations	11,728
R^2	0.30

Notes: (1) Data is from the 2001 National Highway Travel Survey (NTHS). (2) The unit of analysis is a household. (3) A dummy variable indicating that the head of household's age is missing is included. (4) Top 1% set as topcode. (5) Standard errors are clustered by metropolitan area and are reported below the regression coefficient estimate. (6) The omitted category is a household in the Northeast region.

Fig. 1. Relationship between gasoline consumption and MSA size. Notes: gasoline consumption was estimated using the 2001 National Household Transportation Survey. Population is from the US Census.

To estimate the gasoline-related emissions of a marginal household, we again start with the gasoline consumption predicted at the tract level using our coefficients shown in Table 1. We then aggregate census tract gasoline usage up to the metropolitan area, by averaging across census tracts, weighting not by current population levels, but instead by the amount of housing built between 1980 and 2000. If the location of housing in the near future looks like the location of housing in the near past, then the location of recent construction gives us some idea about where new homes will go.

On average, homes built in the last 20 years are associated with 47 more gallons of gasoline per household per year than average homes, which reflects the tendency to build on the urban edge. While we believe that focusing on recent housing patterns adjustment makes sense, it makes little difference to the cross-metropolitan area rankings. The correlation between estimated metropolitan area gasoline consumption using the total population of each census tract and the estimate based on the number of houses built since 1980 is .96.

To convert gallons of gasoline into carbon dioxide emissions, we multiply first by 19.564, which is a standard factor used by the Department of Energy.[13] This conversion factor includes only the direct emissions from a gallon of gasoline, not the indirect emissions associated with refining and delivering gas to the pump, which typically increase the energy use associated with a gallon of gas by 20%.[14] To reflect this, we assume that each gallon of gas is associated with 23.46 lb of carbon dioxide emissions.

3.2. Public transportation

We now turn to the emissions associated with public transportation. There are no adequate individual surveys that can inform us about energy usage by bus and train commuters. Instead, we turn to aggregate data for each of the nation's public transit systems from the National Transit Database.[15] For all of the nation's public transit systems, this data source provides us with information about energy used, which takes the form of gasoline in the case of buses and electricity in the case of rail. The data does not tell us about private forms of public transit, such as private bus lines or taxis or the Las Vegas monorail.

For each bus or rail system, the data set provides us with the zip code of their headquarters. We then assign each zip code to the relevant metropolitan area and sum up all of the gasoline and electricity used by public transit systems within each metropolitan area. This provides us with total energy usage by public transit for each metropolitan area.

To convert energy use into carbon dioxide emissions, we continue to use a factor of 19.546 for gasoline. We again increase that factor by 20% to reflect the energy used in refining and distribution. The conversion for electricity is somewhat more difficult, since electricity is associated with different levels of emissions in different regions of the country. We will therefore be using different conversion factors for electricity in different places, and we will discuss those at length when we get to home electricity usage. By combing emissions from gas and emissions from electricity, we estimate a total emissions figure within the metropolitan area. To convert this to a household-level figure, we divide by the number of households in the metropolitan area.

There are two reasons why the marginal emissions from a new household might not be the same as the average emissions for an existing household. First, the marginal household might be more or less inclined to use public transportation. Second, even if the marginal household uses public transport, we do not know how much extra energy this will entail. Typically, we think of some public transit technologies as having large fixed costs, which could mean that the marginal costs are quite low. However, in some cases, new development may mean that a new bus line is extended to a newer, lower density area, and in this case, the marginal costs might be quite high. Since we lack the data to make an effective estimate of the marginal effect, we will use the average emissions from public transit throughout this paper. Since the emissions from private automobiles are on average 50 times higher than the emissions from driving, the benefits to our overall estimates of improving the accuracy of our public transit emissions measures are likely to be small.

3.3. Household heating

We now turn to the emissions from the two primary household heating sources: fuel oil and natural gas. Fuel oil use is rare in the United States outside of the Northeast, and is an important source of home heating in only a few metropolitan areas. Natural gas is the more common source of home heat. In some areas, electricity

[13] See http://www.eia.doe.gov/oiaf/1605/factors.html.

[14] A typical energy efficiency figure for gasoline is 83%: http://frwebgate.access.gpo.gov/cgi-bin/getdoc.cgi?dbname=2000_register&docid=00-14446-filed.pdf.

[15] http://www.ntdprogram.gov/ntdprogram/.

also provides heat, but we will deal with electricity separately in the next section.

For our purposes we need a large representative sample that provides information by metropolitan area on household heating. The Department of Energy's Residential Energy Consumption Survey is too small of a data set to address our needs.[16] This data set also does not provide each survey respondent's metropolitan area. Instead, we use data from the 2000 Census 5% sample (IPUMS). This data set provides information for each household on its expenditure on electricity, natural gas and fuel oil.

The key problem with the IPUMS data is that we are interested in household energy use, not energy spending. Conveniently, the Department of Energy provides data on prices for natural gas[17] and fuel oil[18] for the year 2000. These prices are at the state level, so we miss variation in prices within the state. We use these prices to convert household energy expenditure to household energy consumption.

One particular problem with the expenditure data is that some renters do not pay for energy directly, but are charged implicitly through their rents (Levinson and Niemann, 2004). These renters will report zero energy expenditures, when they are indeed using electricity and some home heating fuel. Indeed, when we look at the frequency of reported zero expenditure in different metropolitan areas, we find that these tend to be disproportionate among renters and other residents of multi-family houses. In these cases, it is impossible to know whether a zero value for expenditure truly indicates that the household does not consume this particular fuel or whether the household just does not pay directly for that energy. As such, we have the most confidence in the IPUMS data for measuring actual household energy consumption for owners of single family homes. In Appendix B, we discuss how we address this problem.

We use the IPUMS 2000 data to estimate a separate regression for each of the 66 metropolitan areas using the subsample of owners of single family homes:

$$\text{Energy use} = a * \text{Log(income)} + b * \text{household size} + c * \text{age of head} + \text{MSA constant}. \tag{2}$$

For each metropolitan area, we estimate similar regressions for fuel oil and electricity consumption. We then use metropolitan area specific regression coefficients to predict the natural gas and fuel oil consumption for a household with an income of 62,500 dollars and 2.62 members.

We try to correct for individual characteristics, but we do not correct for housing characteristics. After all, we are not attempting to estimate emissions assuming that people in Houston live in New York City apartment buildings. The building sizes in an area are a key component in emissions and we want to include that. Our approach allows for the fact that a household with a fixed set of demographics is likely to live in a larger, newer home if it lived in Houston than it would have chosen if it lived in Boston or New York City, since land prices are higher in the latter cities. Our approach captures the fact that a standardized household will live its life differently depending on the relative prices that it faces in different cities.

Natural gas consumption is driven primarily by climate. Fig. 2 shows the correlation between our estimated natural gas consumption and January temperature. We do not find the correlation coefficient of $-.81$ surprising, but it does suggest that our results are reasonable.

For fuel oil and natural gas, there are again conversion factors that enable us to move from energy use to carbon dioxide emissions. In the case of fuel oil the factor is 22.38 lb of carbon dioxide per gallon

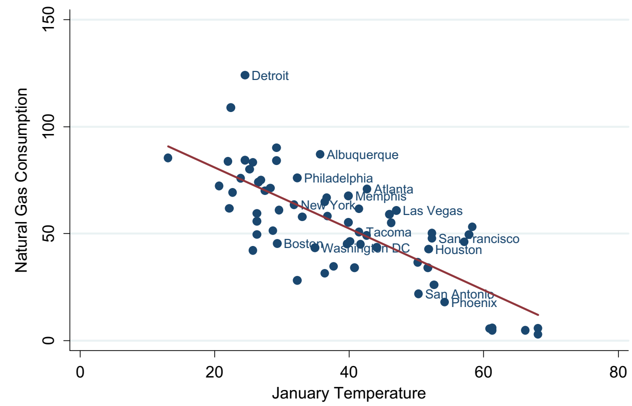

Fig. 2. Relationship between natural gas consumption and January temperature. Notes: natural gas consumption (measured in cubic feet) was estimated using the Integrated Public Use Microdata Series from the 2000 Census, the Department of Energy prices for natural gas, and the Department of Energy's Residential Energy Consumption Survey (RECS) for 2001. January Temperature is from the National Oceanic and Atmospheric Administration.

of fuel oil.[19] We again increase this number by 20% to reflect the energy used in refining and distributing. According to the same source, there are 120.59 lb of carbon dioxide emissions per 1000 cubic feet of natural gas. In this case, there is much less energy involved in distribution so we use this conversion factor without any adjustment. We combine the emissions from natural gas and fuel oil to form an estimate of total home heating emissions.

To examine the impact of a marginal home, we repeat this procedure using only homes built between 1980 and 2000. Since older homes are less fuel efficient, the average home will overstate true energy use, especially in older areas of the country. We use only homes built within the last 20 years to minimize this effect. In principle, we could have used only homes built in the last 5 or 10 years, but our sample sizes become too small if we limit our samples in this way. We will refer to these estimates as our estimates of marginal heating emissions.

3.4. Household electricity

In the case of electricity consumption, we begin with the same IPUMS-based procedure used for fuel oil and natural gas. We use state-wide price data to convert electricity expenditure into consumption in megawatt hours.[20] We then regress estimated electricity consumption on household characteristics by metropolitan area, just as we did for home heating. We also follow the same imputation procedure for owners of multi-family units and all renters. Following this strategy, we predict household annual electricity consumption for each metropolitan area for a standardized household with 2.62 people earning an annual income of $62,500. In the case of electricity, consumption rises most sharply with July temperatures, as shown in Fig. 3. The correlation is relatively strong .61.

The conversion between electricity usage and carbon dioxide emissions is considerably more complicated than the conversion between natural gas or petroleum usage and emissions. If we had a national market for electricity, then it would be appropriate to use a uniform conversion factor, but since electricity markets are regional, we must allow for different conversion factors in different areas of the country. There is considerable heterogeneity in the emissions for megawatt hour of electricity between areas that rely

[16] http://www.eia.doe.gov/emeu/recs/recs2001/publicuse2001.html.
[17] http://www.eia.doe.gov/emeu/states/_seds.html.
[18] http://tonto.eia.doe.gov/dnav/pet/pet_sum_mkt_a_EPD2_PRT_cpgal_a.htm.
[19] http://www.eia.doe.gov/oiaf/1605/factors.html.
[20] http://www.eia.doe.gov/cneaf/electricity/epm/table5_6_b.html.

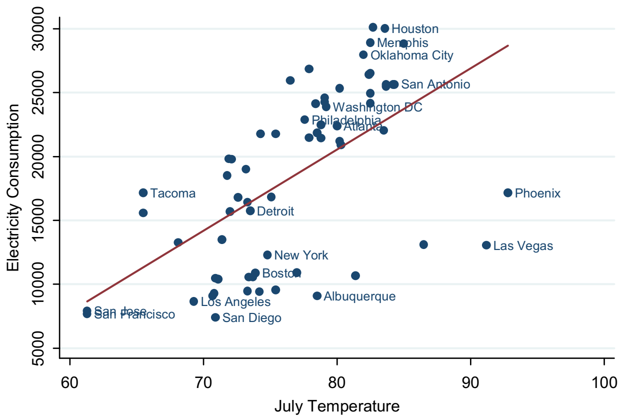

Fig. 3. Relationship between electricity consumption and July temperature. Notes: electricity consumption (measured in kW h) was estimated using the Integrated Public Use Microdata Series from the 2000 Census, the Department of Energy prices for electricity, and the Department of Energy's Residential Energy Consumption Survey (RECS) for 2001. Electricity Consumption was estimated using July Temperature is from the National Oceanic and Atmospheric Administration.

on coal, like the Northeast, and areas that use more hydroelectric energy, like the West.

What geographic area should we use to calculate the emissions related to electricity usage? In principle, one could calculate anything from a national average of emissions per megawatt hour to a block specific figure. Using smaller levels of geography certainly increases the accuracy with which emissions are allocated to electricity usage. However, if electricity is perfectly substitutable between two places, then this precision is somewhat misleading, and irrelevant for estimating the marginal emissions associated with new construction. The relevant consideration is not the actual greenness of the particular area's supplier, but rather the average emissions of the entire area.

For example, consider a setting where there is a clean and a dirty electricity producer in a region, with identical costs of production and plenty of consumers who do not care about the source of their electricity. In equilibrium, both producers will generate the same amount of electricity. A new consumer who buys only from the clean producer will still be associated with the average level of emissions. Since these two providers are perfect substitutes, if a new resident buys only from the clean provider, then someone else will be buying from the dirty provider. For this reason, it makes sense to consider the average emissions within the market not the individual emissions of one particular place.

The North American Electric Reliability Corporation (NERC) has divided the US into eight electricity markets. While electricity within these regions is not perfectly fungible and there is some leakage across NERC regions, there is much more substitutability of electricity within NERC regions than across regions. The difficulties involved in transmitting electricity over long distances mean that electricity in one region cannot readily substitute for electricity in another region. We therefore feel comfortable treating these markets as more or less closed systems (Holland and Mansur, 2008).

We calculate NERC region average emissions data using power plant level data from the Environmental Protection Agency's eGRID, or Emissions and Generation Resource Integrated Database.[21] The eGRID data base contains the emissions characteristics of virtually all electric power in the United States and includes emissions and resource mix data for virtually every electricity-generating power plant in the US eGRID uses data from 24 different federal data sources from three different federal agencies: EPA, the Energy Information Administration (EIA), and the Federal Energy Regulatory Commission (FERC). Emissions data from EPA are integrated with generation data from EIA to create the key conversion factor of pounds of carbon dioxide emitted per megawatt hour of electricity produced (lbs/MW h).

Using eGRID data from 2004, we calculate the emissions for megawatt hour for each of the NERC regions. There is remarkable heterogeneity across these regions (Holland and Mansur, 2008). For example, San Francisco is located in a NERC region that generates 1000 lb of carbon dioxide for each megawatt hour of electricity. In contrast, Philadelphia is located in a NERC region where the average power plant in the region generates 1600 lb of carbon dioxide for each megawatt hour.

We then use these conversion factors to turn household electricity usage into carbon dioxide emissions for each metropolitan area. We use the same conversion factor to handle the electricity consumption of commuter rails. To consider the impact of the marginal home, as above, we restrict our IPUMS estimates to homes built only between 1980 and 2000.

3.5. Overall household rankings

We finally turn to an overall ranking of metropolitan areas based on carbon dioxide emissions. Table 2 lists the 66 largest metropolitan areas for which we have data. The first column shows carbon dioxide emissions from predicted gasoline consumption within each metropolitan area. There is considerable range in the consumption of gasoline at the metropolitan area level. The New York metropolitan area is estimated to use the least gasoline, which reflects its high degree of employment and population concentration and its relatively heavy use of public transportation. Greenville, South Carolina, is estimated to use the most gasoline. The gasoline-related emissions in Greenville are almost twice as high as the gasoline-related emissions in the New York area.

The second column reports our results on per household energy emissions due to public transportation. This column adds together rail and bus emissions and converts both by appropriate factors to arrive at carbon dioxide emissions. There is, of course, considerable heterogeneity. Emissions from public transportation in New York City are more than three tons of carbon dioxide from public transit per capita.[22] However, even in New York, these emissions are relatively modest relative to the contributions of cars, since public transportation shares infrastructure, like buses, and uses electricity.

The third column gives our results on fuel oil and natural gas. Again, the results show a fair amount of regional disparity. Detroit leads the country in home heating emissions and Boston is a close second. Much of the West has almost no emissions from home heating. In general, places that use fuel oil have much higher emissions than places that use only natural gas, which explains why emissions from this source are much lower in Chicago than in Detroit.

The fourth column shows electricity consumption and the fifth column shows the NERC-based conversion factor for converting electricity into emissions. To calculate electricity related emissions in each area, the fourth and fifth columns need to be multiplied together.[23] We show these columns separately to illustrate the role

[21] See http://www.epa.gov/cleanenergy/egrid/index.htm.

[22] We do not have data on energy consumption from public transit in Las Vegas.

[23] Households use electricity not only at home but also where they shop and work. In results that are available on request, we have used the 2003 Commercial Building Energy Survey. This building level data set collects information on roughly 5000 buildings across the United States. While this data set does not have metropolitan area identifiers, it does provide information on the heating degree days and cooling degree days at the location of each of the buildings. We regress building energy consumption per worker on building type dummies and these climate measures. Using city level climate data from Burchfield et al. (2006), we predict commercial building energy consumption per worker for each metropolitan area. The cross-metropolitan area correlation between commercial energy consumption prediction and our residential energy consumption measure is .65.

Table 2
Annual standardized household CO_2 emissions.

MSA	Emissions from driving (lbs of CO_2)	Emissions from public transportation (lbs of CO_2)	Emissions from home heating (lbs of CO_2)	Electricity (MW h)	NERC power plant emissions factor (lbs of CO_2 per MW h)	Carbon dioxide emissions cost ($ per year)	Standard error ($ per year)
San Diego, CA	24,774	689	5994	7.18	1007	1148	14.87
San Francisco, CA	23,970	1675	6784	7.03	1007	1152	17.17
San Jose, CA	23,649	2058	7030	7.75	1007	1175	16.03
Providence, RI	22,562	1273	12,965	7.35	1185	1177	13.24
Los Angeles, CA	23,553	1062	6439	8.43	1007	1188	17.91
Sacramento, CA	25,534	458	6875	9.07	1007	1237	13.96
Hartford, CT	23,092	1539	13,752	8.09	1185	1239	17.71
Riverside, CA	26,380	42	6461	9.27	1007	1246	13.64
Boston, MA	22,870	2276	14,019	7.92	1185	1253	11.91
Tucson, AZ	26,363	616	4535	12.25	1007	1270	14.65
Buffalo, NY	24,400	1124	11,481	6.97	1185	1277	14.04
Las Vegas, NV	24,257	0	6714	13.25	1007	1280	15.05
Albuquerque, NM	25,229	648	10,741	8.92	1007	1296	14.83
Fresno, CA	25,662	951	7634	10.48	1007	1304	14.62
Rochester, NY	25,732	902	11,377	7.27	1185	1306	16.64
Phoenix, AZ	25,543	75	2627	16.39	1007	1307	13.71
Denver, CO	25,159	1374	10,494	10.10	1007	1336	13.76
Portland, OR	25,915	2098	5854	13.58	1007	1347	13.90
Syracuse, NY	26,744	574	11,588	8.07	1185	1347	17.78
Albany, NY	26,277	1054	11,653	8.05	1185	1352	17.21
New York, NY	18,081	6386	12,503	7.83	1400	1379	6.33
Salt Lake City, UT	25,491	3104	11,146	10.15	1007	1406	13.90
Tacoma, WA	26,169	430	5942	18.36	1007	1422	14.48
Seattle, WA	25,234	5948	6762	15.50	1007	1477	13.79
Pittsburgh, PA	25,591	2093	12,313	9.67	1614	1600	15.88
Cleveland, OH	26,784	1733	10,980	10.90	1614	1633	13.00
Akron, OH	28,604	768	10,652	10.91	1614	1644	16.94
Scranton, PA	27,611	282	13,173	10.19	1614	1651	18.64
Fort Lauderdale, FL	25,392	1124	539	17.47	1427	1695	18.26
Philadelphia, PA	22,784	3993	13,688	12.30	1614	1698	9.59
Sarasota, FL	28,155	510	532	16.29	1427	1701	14.55
Milwaukee, WI	26,315	1291	10,117	9.35	1614	1726	12.73
Columbus, OH	27,997	278	9291	10.14	1614	1727	14.94
St. Louis, MO	28,105	1267	8749	13.54	1472	1737	13.98
West Palm Beach, FL	27,233	616	677	17.82	1427	1738	15.40
Tampa, FL	28,034	742	673	17.36	1427	1743	14.88
Cincinnati, OH	27,537	770	8784	12.83	1543	1764	12.09
Miami, FL	24,187	4689	896	17.92	1427	1768	21.69
Chicago, IL	24,278	5221	10,374	9.83	1614	1781	15.21
Orlando, FL	28,174	1361	734	18.48	1427	1789	14.44
Norfolk, VA	27,091	1078	5561	16.01	1472	1792	15.43
New Orleans, LA	24,899	663	4964	19.05	1472	1795	19.18
Raleigh-Durham, NC	29,922	495	5797	14.55	1472	1798	13.96
Greensboro, NC	31,300	216	4747	14.53	1472	1799	15.09
Grand Rapids, MI	29,248	572	14,362	8.23	1614	1811	18.57
Charlotte, NC	30,820	1084	5963	14.25	1472	1825	14.58
Kansas City, MO	28,763	644	10,319	13.50	1561	1830	16.51
San Antonio, TX	27,694	1 929	4110	15.74	1555	1832	15.24
Washington, DC	25,918	4729	5674	13.72	1543	1832	18.46
Baltimore, MD	26,540	2135	5405	13.78	1614	1835	17.57
Richmond, VA	29,459	771	4101	16.87	1472	1835	15.23
Louisville, KY	27,880	884	8538	14.92	1543	1837	13.19
Greenville, SC	32,169	130	4964	15.25	1472	1841	16.90
Dayton, OH	28,888	986	9027	12.69	1614	1847	17.89
Tulsa, OK	29,091	353	8729	13.69	1561	1855	14.80
Detroit, MI	27,403	889	16,511	9.23	1614	1862	13.22
Atlanta, GA	29,425	1121	8851	14.63	1472	1866	13.96
Minneapolis-St. Paul, MN	27,427	143	10,990	10.12	1819	1866	13.51
Indianapolis, IN	29,222	534	10,665	12.80	1614	1888	16.62
Austin, TX	29,134	1595	4613	16.58	1555	1892	15.02
Dallas, TX	27,323	1723	6100	17.81	1555	1926	16.30
Houston, TX	27,333	1447	5344	18.74	1555	1932	15.98
Birmingham, AL	30,041	227	7759	16.64	1472	1937	14.82
Nashville, TN	30,495	473	6699	17.21	1472	1954	14.71
Oklahoma City, OK	28,953	332	8710	16.41	1649	2005	14.73
Memphis, TN	28,440	1073	8438	18.70	1472	2015	14.43

Notes: (1) Data is from the Integrated Public Use Microdata Series from the 2000 Census, the 2001 National Household Transportation Survey (NHTS), the Department of Energy, the National Transit Database, the 2001 Residential Energy Consumption Survey (RECS), and the Environmental Protection Agency's Emissions and Generation Resource Integrated Database (eGRID). (2) See text for detailed descriptions of the data calculations.

of electricity usage versus the role of clean electricity production. New Orleans is the leader in electricity usage, while residents of Buffalo consume the least electricity. San Francisco has the second lowest electricity usage in our data.

The sixth column sums together all of the different sources of carbon dioxide emissions. The table is ordered by the amount of these emissions. California's cities are blessed with a temperate climate and they use particularly efficient appliances and produce electricity in particularly clean ways. Four of the five cities with the lowest emissions levels are all in California. Providence, Rhode Island ranks in the top five due to its low electricity use.

The high emissions cities are almost all in the South. These places have large amounts of driving and very high electricity usage. Their electricity usage is also not particularly clean. Texas is particularly well represented among the places with the highest levels of emissions. Memphis has the absolute highest level among our 66 metropolitan areas. Indianapolis and Minneapolis are the northernmost places among our ten highest emission metropolitan areas.

New construction in the Northeast is generally between those extremes. These places use moderate amounts of electricity. They drive less than Californians, but use large amounts of fuel oil. The Midwest looks generally similar to the Northeast, but larger amounts of driving push gasoline emissions up.

In column seven, we multiply total emissions by 43 dollars per ton to find the total emissions-related externality associated with an average home in each location. The 43 dollar number is somewhat arbitrary, and we are using it purely for illustrative purposes. It is conservative relative to the Stern report (2008), which suggests a cost of carbon dioxide that is twice this amount, but it is considerably more aggressive than the numbers used by Nordhaus (2007). Tol (2005) is one meta-study that also suggests that this number may be somewhat too high while our number is in the middle of the range in Metcalf (2007).[24] Using this figure, the range of costs associated with each home goes from $1148 dollars in San Diego to more than $2015 dollars in Memphis. This $867 dollar gap is an annual flow, and at a discount rate of 5%, this would suggest a tax of 17,340 dollars on every new home in Memphis relative to San Diego.[25] The last column gives standard errors for these cost estimates. The procedure for estimating these standard errors is detailed in the statistical appendix.[26] The standard errors of the carbon emissions (measured in tons) equal the standard errors of the emissions costs divided by 43.

Table 3 shows the 66 Metropolitan Area ranking based on the subset of households who live in homes built between 1980 and 2000. Table 3's structure is identical to Table 2 but Table 3 provides an estimate of how average emissions vary across metropolitan areas for a standardized household who lives in housing built between 1980 and 2000. This is useful information for determining whether within MSA growth patterns are shrinking the city's average footprint.

The differences between the two tables tend to offset each other. People who live in new homes consume more gasoline, which reflects the tendency of new growth to be in the suburbs. However, new homes are more energy efficient and therefore have lower emissions from home heating. In general, we find that this ranking based on recent growth is highly positively correlated with the average rankings reported in Table 2.

The energy use differences between metropolitan areas are quite large. Our estimate is that a new house in coastal California is associated with two-thirds or less of the emissions associated with a new house in Houston or Oklahoma City. These differences suggest that changing urban development patterns can have potentially large impacts on total carbon emissions. Since residential and personal transportation are associated with about 40% of total emissions, a 33% reduction in these sources would reduce total US emissions by 13%. Of course, any policy interventions would impact the flow of new housing, rather than the stock, so changes in urban development patterns would only reduce emissions gradually.

Our cost estimates suggest optimal location-specific taxes on development, in the absence of other carbon emission taxes. The 600 dollar difference in emissions costs between the coastal California areas and Memphis suggests a flow tax of 600 dollars per year for each household in Memphis. This is not a small number. If the tax were paid in a single lump sum payment, of perhaps $12,000, then this would represent a sizable increase in the cost of living in Memphis. The US Census tells us that the median value of a home in Memphis in 2006 was 91,000 dollars. Of course, the model suggests that a direct carbon tax would improve social welfare more than any location tax, so we believe that the main value of our results is only to suggest the external costs associated with moving to places like Memphis.

To study the cross-MSA correlates of greenhouse gas production, we present five separate OLS regressions in Table 4. In each of these regressions, the explanatory variables include the logarithm of average city income, the logarithm of city population, average January temperature and average July temperature. We also include a measure of the share of city centralization: the share of the population within five miles of the city center. The first column shows the correlates of private transportation related emissions. Income is uncorrelated with gasoline usage at the metropolitan level. At the individual level, there is a strong connection between gasoline consumption and income, but these estimates are supposed to correct for that relationship and they seem to do that. Larger metropolitan areas have somewhat less driving, which reflects the fact that these cities are somewhat denser. As the share of population within five miles of the city center increases by 10%, carbon dioxide emissions from driving decreases by 1300 lb. Finally, places with warm Januarys have less driving, but places with hot Julys have more driving. These correlations are presumably spurious, and reflect other variables, like the degree of sprawl, associated with these weather variables.

The next regression shows the correlates of public transit emissions. In this case, city population is the only variable that is strongly correlated with emissions. Bigger cities are more likely to have extensive public transit systems. There is also a weak correlation between this outcome and the concentration of population within five miles of the city center.

The third regression looks at the relationship between home heating-related emissions and the area-level variables. There is an extraordinarily strong negative correlation between this variable and January temperature, which was discussed above (also see Ewing and Rong, 2008). Lower July temperatures also weakly increase home heating emissions. None of the other variables are strongly correlated with this outcome variable. The power of temperature to predict home heating emissions explains why the R^2 for this regression is higher than for any of the other regressions in this table.

The fourth regression correlates electricity related emissions with our independent variables. Areas that are more geographi-

[24] It is relevant to note that carbon tax policy proposals have suggested taxes per ton of carbon dioxide roughly in this range. Metcalf (2007) proposes a bundled carbon tax and a labor tax decrease. As shown in his Fig. 6, he proposes that the carbon tax start at $15 per ton (in year 2005 dollars) now and rise by 4% a year. Under this proposal, the carbon tax per ton of carbon dioxide would equal $60 per ton (in year 2005 dollars) by 2050.

[25] We recognize that we are assuming that new migrants to Memphis would produce the same average carbon footprint as the incumbents.

[26] The standard errors for the predictions are based on the sampling variation in the 2001 NHTS data set as reported in Table 1. We are assuming that the large sample sizes in the IPUMS data set minimize the sampling error in our predictions of the other entries in Table 2.

Table 3
Annual standardized household CO_2 emissions for households living in homes less than 20 years old.

MSA	Emissions from driving (lbs of CO_2)	Emissions from public transportation (lbs of CO_2)	Emissions from home heating (lbs of CO_2)	Electricity (MW h)	NERC power plant emissions factor (lbs of CO_2 per MW h)	Carbon dioxide emissions cost ($ per year)	Standard error ($ per year)
Los Angeles, CA	23,766	1062	5558	8.60	1007	840	17.88
San Diego, CA	25,183	689	5975	7.34	1007	844	16.20
San Francisco, CA	24,777	1675	5765	7.62	1007	858	17.13
San Jose, CA	24,004	2058	6055	7.85	1007	860	19.96
Sacramento, CA	25,827	458	6636	9.50	1007	913	13.93
Riverside, CA	26,761	42	6413	9.34	1007	916	13.65
Fresno, CA	25,587	951	7126	10.60	1007	953	14.46
Tucson, AZ	27,062	616	4106	13.02	1007	965	14.65
Las Vegas, NV	24,667	0	7347	12.97	1007	969	15.08
Phoenix, AZ	26,339	75	2168	17.04	1007	983	14.68
Albuquerque, NM	25,764	648	10,500	9.03	1007	989	34.98
Rochester, NY	26,920	902	10,084	7.67	1185	1011	16.73
Buffalo, NY	26,539	1124	10,866	7.84	1185	1028	14.05
Denver, CO	26,147	1374	10,152	10.47	1007	1037	13.82
Portland-Vancouver, OR	26,520	2098	6665	13.16	1007	1044	14.11
Providence, RI	25,648	1273	12,213	8.00	1185	1045	14.64
Syracuse, NY	27,637	574	10,441	8.82	1185	1056	17.80
New York, NY	20,480	6386	10,258	8.78	1400	1062	6.34
Albany, NY	28,618	1054	10,462	8.78	1185	1087	17.24
Tacoma, WA	26,877	430	6120	17.05	1007	1088	14.48
Salt Lake City, UT	26,282	3104	10,870	10.84	1007	1100	13.46
Hartford, CT	27,047	1539	12,245	8.89	1185	1105	17.71
Boston, MA	26,062	2276	13,023	9.18	1185	1123	11.75
Fort Lauderdale, FL	25,992	1124	354	17.97	1427	1142	18.14
Milwaukee, WI	28,020	1291	8957	9.71	1614	1160	12.93
Sarasota, FL	29,037	510	584	16.94	1427	1168	14.92
Seattle, WA	25,838	5948	7425	15.45	1007	1177	13.88
Columbus, OH	29,515	278	8602	10.43	1614	1187	14.15
Tampa, FL	28,885	742	707	17.48	1427	1189	14.79
West Palm Beach, FL	27,963	616	583	18.58	1427	1197	16.08
Miami, FL	25,056	4689	697	17.86	1427	1203	21.58
Pittsburgh, PA	28,075	2093	9713	10.40	1614	1219	15.89
Orlando, FL	28,838	1361	665	18.50	1427	1231	14.36
Greensboro, NC	31,442	216	4169	14.58	1472	1232	14.74
Grand Rapids, MI	30,236	572	13,141	8.36	1614	1235	17.96
Raleigh, NC	30,433	495	5446	14.56	1472	1243	14.54
Chicago, IL	26,088	5221	10,113	10.17	1614	1243	15.53
Norfolk, VA	27,606	1078	5587	16.47	1472	1258	15.40
Charlotte, SC	31,159	1084	5439	14.19	1472	1259	14.40
Cincinnati, OH	29,407	770	6742	14.09	1543	1261	11.50
Minneapolis-St. Paul, MN	29,151	143	10,513	10.45	1819	1264	13.63
San Antonio, TX	28,810	1929	2638	16.49	1555	1269	15.26
Greenville, SC	32,568	130	4104	15.28	1472	1275	19.71
Dayton-Springfield, OH	29,463	986	7155	13.47	1614	1276	17.09
Akron, OH	30,454	768	9662	11.47	1614	1277	15.22
St. Louis, MO-IL	29,811	1267	7366	14.39	1472	1282	12.68
Baltimore, MD	28,347	2135	3391	16.07	1614	1286	17.64
New Orleans, LA	26,164	663	3129	20.45	1472	1291	19.25
Scranton, PA	30,117	282	10,117	12.24	1614	1296	18.71
Cleveland, OH	29,298	1733	10,032	12.27	1614	1309	13.28
Richmond, VA	29,521	771	3790	18.23	1472	1310	14.69
Tulsa, OK	30,841	353	7805	14.12	1561	1312	14.85
Detroit, MI	29,473	889	14,957	9.75	1614	1313	13.05
Washington, DC	27,511	4729	5228	15.48	1543	1319	18.65
Austin, TX	29,717	1595	4419	16.49	1555	1320	15.07
Indianapolis, IN	30,299	534	8949	13.48	1614	1323	26.66
Kansas City, MO	30,235	644	9042	14.01	1561	1328	17.23
Louisville, KY	30,231	884	6965	15.63	1543	1337	18.52
Atlanta, GA	30,192	1121	8555	15.20	1472	1338	14.01
Philadelphia, PA	25,426	3993	10,831	14.16	1614	1357	9.66
Dallas, TX	28,155	1723	5253	18.53	1555	1375	16.31
Birmingham, AL	32,491	227	5920	17.21	1472	1376	15.96
Nashville, TN	31,959	473	7006	16.69	1472	1376	15.65
Houston, TX	28,216	1447	5148	19.30	1555	1394	16.54
Oklahoma City, OK	31,312	332	8058	16.94	1649	1454	15.12
Memphis, TN	29,547	1073	8166	19.63	1472	1455	14.41

Notes: (1) Data is from the Integrated Public Use Microdata Series from the 2000 Census, the 2001 National Household Transportation Survey (NHTS), the Department of Energy, the National Transit Database, the 2001 Residential Energy Consumption Survey (RECS), and the Environmental Protection Agency's Emissions and Generation Resource Integrated Database (eGRID). (2) See text for detailed descriptions of the data calculations.

Table 4
Regression table.

	(1)	(2)	(3)	(4)	(5)
	Emissions from driving	Emissions from public transportation	Emissions from home heating	Emissions from electricity	Total emissions
Log(income)	1373 (1945)	1123 (1351)	−1901 (2215)	3745 (6452)	4340 (7051)
Log(population)	−2514 (411)	1193 (285)	1084 (468)	−2337 (1362)	−2573 (1489)
Share of MSA employment within 5 miles of the city center	−13,079 (2432)	2587 (1690)	4215 (2770)	−21,618 (8068)	−27,896 (8817)
January mean temperature	−71 (17)	−4 (12)	−191 (19)	−15 (56)	−280 (62)
July mean temperature	107 (39)	−11 (27)	−92 (44)	612 (128)	615 (140)
Constant	46,439 (20,068)	−27,651 (13,940)	25,966 (22,857)	−30,688 (66,569)	14,066 (72,749)
Observations	66	66	66	66	66
R^2	0.56	0.38	0.73	0.41	0.41

Notes: (1) Dependent variables are the total pounds of CO_2 emissions from the listed source. (2) The dependent variables are the marginal emissions, that is, emissions calculated for housing built between 1980 and 2000. See Table 3. (3) The unit of analysis is a metropolitan area. (4) Standard errors are reported in parentheses. (5) Data is from the Integrated Public Use Microdata Series from the 2000 Census, the 2001 National Household Transportation Survey (NHTS), the Department of Energy, the National Transit Database, the 2001 Residential Energy Consumption Survey (RECS), the Environmental Protection Agency's Emissions and Generation Resource Integrated Database (eGRID), and the National Oceanic and Atmospheric Administration.

cally concentrated have lower levels of electricity usage and lower emissions. The strongest determinant of home electricity usage in this regression, unsurprisingly, is July temperature. Still, the ability of the weather to explain electricity is weaker than the ability of the weather to explain home heating emissions.

Finally, the fifth regressions look at the correlates of total emissions. In this case, all of the variables except for city income are statistically significant. More populous cities have lower emissions, and this is being driven both by less electricity usage and by less driving. More decentralized cities have higher emissions, and this reflects less electricity and less driving. Places with milder Januarys have lower emissions, which is the result of less use of artificial heat. Places with hotter Julys have higher emissions, reflecting the electricity needed to run air conditioners.

As such, these regressions suggest that there are several different variables associated with lower levels of emissions at the city level. Older dense cities have lower emissions, but not if they are particularly cold. The temperate Sunbelt uses little electricity, but not the places with particularly hot summers.

What is the connection between low greenhouse gas emissions and city growth? Fig. 4 shows the correlation between these marginal cost estimates and development in the area since 2000. Our dependent variable is the ratio between average annual housing permits in the area since the year 2000 and the total stock of housing in these places in the year 2000. This measure captures the extent to which the area is building new homes.

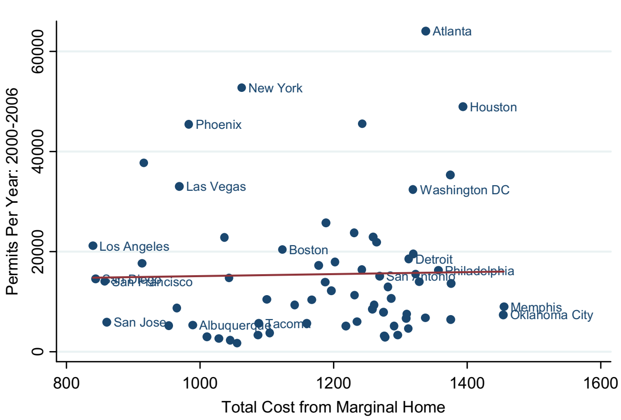

Fig. 4. City growth and total emission costs. Notes: housing permit data is from the US Census. total cost from marginal home was estimated using data from the Integrated Public Use Microdata Series from the 2000 Census, the 2001 National Household Transportation Survey (NHTS), the Department of Energy, the National Transit Database, the 2001 Residential Energy Consumption Survey (RECS), and the Environmental Protection Agency's Emissions and Generation Resource Integrated Database (eGRID).

The overall relationship is basically flat, which suggests that current development patterns are neutral towards emissions. Unfortunately, that conclusion may be a bit optimistic because the correlation becomes significantly positive if we weight by the initial population of the area. The flat relationship that we see is driven primarily by Las Vegas and Phoenix, two areas that have high levels of growth and low levels of emissions. Without those areas, the relationship between growth and emissions becomes more strongly positive.

If moderate temperatures lower carbon emissions and lower energy costs, then why are not people moving to places with more temperate climates? One possible reason for the weak relationship between new construction and per-household emissions is that places with benign climates also have more stringent land use regulations. As Fig. 5 shows, there is a strong negative association between carbon dioxide emissions and the Wharton Land Use Regulation Index, which is discussed in detail in Gyourko et al. (2008).[27] The aim of the index is to capture a wide range of policies all of which may increase the costs of local development, of which limitations on density are only one component.

Glaeser and Gyourko (2008) report a −.38 correlation between the index and construction between 2000 and 2006. Places with the least emissions tend to regulate housing most heavily.[28] Land use regulation is strongly negatively correlated with both emis-

[27] Gyourko et al. (2008) describe their index: "This aggregate measure is comprised of eleven subindexes that summarize information on the different aspects of the regulatory environment. Nine pertain to local characteristics, while two reflect state court and state legislative/executive branch behavior. Each index is designed so that a low value indicates a less restrictive or more *laissez faire* approach to regulating the local housing market. Factor analysis is used to create the aggregate index, which then is standardized so that the sample mean is zero and the standard deviation equals one."

[28] One possible explanation for this correlation is that liberal cities both regulate energy efficiency and housing supply. For evidence on the latter see Kahn (2009) . Since the early 1970s, California has been an energy efficiency leader. In 1968, per-capita electricity consumption in California roughly equaled the nation's per-capita electricity consumption. Today, California's per-capita electricity consumption is forty percent lower than the nation's per-capita consumption. In late 2006, Governor Schwarzenegger signed AB32 into law. This legislation commits California to sharply reduce its greenhouse gas emissions by the year 2050.

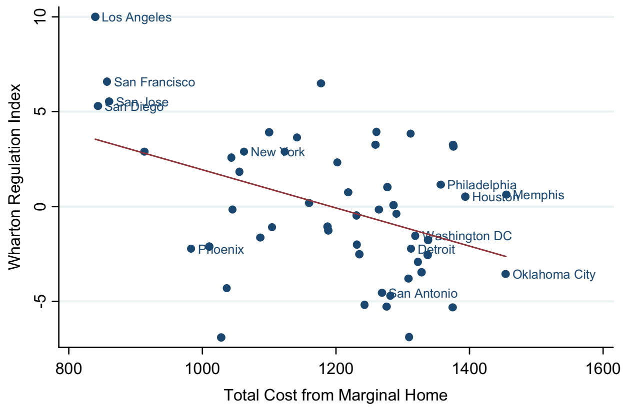

Fig. 5. Wharton Regulation Index and total emissions costs. Notes: the Wharton Regulation Index is discussed in detail in Gyourko et al. (2008). Total cost from marginal home was estimated using data from the Integrated Public Use Microdata Series from the 2000 Census, the 2001 National Household Transportation Survey (NHTS), the Department of Energy, the National Transit Database, the 2001 Residential Energy Consumption Survey (RECS), and the Environmental Protection Agency's Emissions and Generation Resource Integrated Database (eGRID).

sions and growth, but future work will be needed to ascertain with either relationship is causal.[29] For example, land use regulation is correlated with other variables, like hilliness, that also restrict construction (Saiz, forthcoming).

The one interpretation of Fig. 5 that we can clearly reject is that land use regulations are generating lower carbon emissions. Climate explains much of the differences in emissions across areas, and controlling for a city's weather, we find no correlation between the Wharton Regulation Index and our estimates of the city specific carbon emissions.

If the negative correlation between land-use restrictions and new development is pure happenstance, and land use regulations do not limit growth, then the correlation between land-use restrictions and carbon emissions is a mere curiosity. If, however, land-use restrictions do in fact restrict land use, then they are particularly restricting development in the parts of the country with the lower carbon emissions.[30] In that case, land-use restrictions, often allegedly implemented for environmental reasons, may be having the ironic effect of moving development from low emissions places, like California, to high emissions places, like Texas.

4. Greenhouse gas emissions within metropolitan areas

In the previous section, we focused on cross-metropolitan area implications of greenhouse gas emissions. We now look within metropolitan areas, and focus on energy use differences between central cities and suburbs. After all, locating in central cities generally involves far less driving and living in smaller apartments. Since these choices are associated with fewer greenhouse gas emissions, they should also be seen as having fewer negative externalities.

Our approach is again to estimate the average energy consumption associated with locating in different areas, holding a household's income and size constant, but not controlling for other choices like housing characteristics. Living in a larger house is a major part of moving to the suburbs for many people, and that should be captured in the environmental impact of suburbanization. We will use the same data sources and the same methodology as above, but we now focus on the differences between central city and suburban locations.

To keep definitions constant across data sources, we use the Census definition of Central City status, which we have for both census tracts and in the IPUMS. We exclude those data points that do not provide us with a central city identifier. This reduces our set of metropolitan areas down to 48. Sample sizes are unfortunately too small for us to provide robust estimates of emissions for the marginal home within metropolitan areas. As a result, we look only at the emissions associated with an average home.

To provide estimates of gasoline consumption in central cities and suburbs, we continue to use the regression results reported in Table 1 based on the 2001 National Household Travel Survey. This regression enables us to estimate the level of gasoline usage that a standardized household would purchase in each census tract. We then average all of the predicted gas usage numbers in census tracts that are in Central City PUMAs to form our estimate of Central City gasoline consumption. We do the same thing for suburban census tracts to form our estimate of suburban gasoline consumption. We continue to multiply gasoline usage by 23.47 to get total emissions.

As before, we compute gasoline usage for both marginal and average houses. We calculate average household gas consumption by averaging across census tracts using the total number of households in each census tract. We calculate marginal household gas consumption by averaging across census tracts, weighting them by the number of households built in the last 10 years.

In the case of public transportation, we again calculate the total amount of emissions in the metropolitan area. We then allocate those emissions on the basis of public transportation usage. We calculate the total number of households in the central city and suburban commuters who use public transportation. We divide the total public transit emissions by this quantity to find the average public emissions per household that commutes using public transportation. We then multiply this number by the share of households in the suburbs and central city respectively that commute using public transportation to estimate the amount of public transit emissions associated with central city and suburban households.

For fuel oil and natural gas, we continue to use our IPUMS methodology of converting spending into energy use. In this case, the methodology is very dependent on central city and suburban residents facing the same fuel prices. We estimate our regressions separately for each metropolitan area, and in this case we also estimate an indicator variable that takes on a value of one if the household is in the suburbs. This indicator variable provides us an estimate of how much extra fuel is being consumed in suburban areas. We continue to multiply fuel and gas usage by the standard conversion measures to turn them into emissions.

We use the same procedure for electricity. We regress estimated electricity consumption on personal characteristics and a dummy variable that indicates a suburban location. We use the coefficient on that dummy variable as our estimate of the extra electricity associated with suburban living. We multiply this dummy variable by the NERC electric utility emissions factor to calculate the total emissions difference associated with electricity in the central cities and the suburbs. As discussed in the heating section above, we perform a correction using the 2001 RECS data to address the problem that renters and owners in multi-family units may not pay for their own electricity or home heating.

The suburban versus center city differentials are reported in Table 5. This table reports estimates for major metropolitan areas for which the IPUMS reports within metro area geography such that both center city residents and suburban residents can be identified. This yields a sample of 48 metropolitan areas. The first column shows the results for gasoline consumption. The city-suburb gap,

[29] In fact, California passed SB 375 in 2008 with the intent of reducing its cities' carbon footprint through changes in land use regulation (see http://www.planning-report.com/tpr/?module=displaystory&story_id=1257&format=html).

[30] We are confident that such cities could grow and continue to have a low carbon footprint. Pre-existing energy efficiency regulations would also apply to the new housing and new residents who would move into the area.

Table 5
Suburb-city differences in CO_2 output emissions.

MSA	Suburb-city difference in emissions from driving (lbs of CO_2)	Suburb-city difference in emissions from public transportation (lbs of CO_2)	Suburb-city difference in emissions from home heating (lbs of CO_2)	Suburb-city difference in electricity (lbs of CO_2)	Suburb-city difference in carbon dioxide emissions ($ per year)	Suburb-city standard error ($ per year)
New York, NY	6150	−2367	5650	4015	289.16	9.68
Nashville, TN	7880	−649	986	3911	260.74	25.15
Atlanta, GA	6593	−1242	958	5676	257.69	23.37
Boston, MA	6691	−1091	4460	1837	255.82	17.73
Philadelphia, PA	6884	−2286	838	4926	222.78	13.96
Washington, DC	5436	−2280	140	5757	194.64	29.18
Hartford, CT	5392	−2905	3926	1689	174.21	25.76
San Francisco, CA	4246	−939	2678	2078	173.35	25.66
Minneapolis-St. Paul, MN	5314	−105	−225	2960	170.77	21.11
Houston, TX	2794	−561	676	4726	164.13	23.33
Raleigh-Durham, NC	3011	−182	−1839	5996	150.19	21.48
Memphis, TN	3559	−423	252	3529	148.72	21.91
Tulsa, OK	4959	−161	−771	2755	145.80	23.13
Milwaukee, WI	4624	−860	140	2466	136.96	20.18
Baltimore, MD	6248	−1647	−3674	5417	136.40	28.36
Dallas, TX	4040	−986	−884	4009	132.86	23.96
Providence, RI	4427	−982	1615	1067	131.74	20.89
Portland, OR	2965	−553	169	3362	127.76	20.46
Richmond, VA	4475	−995	−3478	5873	126.29	22.04
Cincinnati, OH	2848	−383	−2281	5424	120.58	17.40
Syracuse, NY	2043	−204	1335	2091	113.18	25.27
Cleveland, OH	4396	−1002	−2113	3864	110.60	19.62
Buffalo, NY	4245	−813	124	1558	109.95	20.10
Seattle, WA	2894	−2608	1282	3309	104.87	20.58
Norfolk, VA	2997	−295	−83	2226	104.17	22.48
Charlotte, SC	2937	−604	−248	2671	102.26	21.27
San Antonio, TX	3589	−388	−911	2331	99.34	23.54
Austin, TX	4106	−784	−293	1415	95.53	23.92
St. Louis, MO	4296	−1378	−1377	2742	92.06	19.39
Akron, OH	3661	−369	−1022	1707	85.51	23.20
Sacramento, CA	2185	−101	201	1681	85.27	20.56
Phoenix, AZ	3675	−94	−1497	1835	84.25	21.34
Chicago, IL	5577	−2624	−219	1102	82.48	24.03
Greensboro, NC	2199	−60	−3340	4220	64.91	21.06
Denver, CO	2503	−641	150	934	63.34	20.65
Oklahoma City, OK	1086	−115	−192	1726	53.86	21.02
Fresno, CA	1438	−92	267	785	51.55	20.56
Kansas City, MO	2705	−542	−1625	1743	49.03	25.54
Rochester, NY	2662	−554	−1001	1162	48.80	23.85
Grand Rapids, MI	1528	−183	−1172	1870	43.94	25.65
New Orleans, LA	3391	−474	−1507	407	39.06	27.77
Riverside, CA	1176	−8	685	−695	24.88	19.49
Dayton, OH	2918	−527	−2893	1534	22.20	24.05
Pittsburgh, PA	5824	−1819	−3744	318	12.43	23.14
Tampa, FL	2931	−560	−873	−1239	5.57	22.52
Tacoma, WA	3043	−134	−365	−2428	2.49	21.51
Los Angeles, CA	691	−229	−119	−2455	−45.42	25.36
Detroit, MI	4475	−1214	−6800	−48	−77.12	19.62

Notes: (1) Data is from the Integrated Public Use Microdata Series from the 2000 Census, the 2001 National Household Transportation Survey (NHTS), the Department of Energy, the National Transit Database, the 2001 Residential Energy Consumption Survey (RECS), and the Environmental Protection Agency's Emissions and Generation Resource Integrated Database (eGRID). (2) See text for detailed descriptions of the data calculations.

in Table 5, ranges from 691 lb of carbon dioxide (about 30 gallons of gas) in Los Angeles to 10 times that amount in Philadelphia. Interestingly, there are large gaps in gas emissions both in older cities, where people in the central city take public transportation, and in newer cities, where everyone drives but people in the suburbs drive much more.

In the second columns of Table 5, we turn to public transportation related emissions. Hartford has the largest central city-suburb gap in these emissions (2900 lb of carbon dioxide), followed by Chicago, Seattle, then New York. Riverside has almost no gap. While public transportation made little difference to the metropolitan area figures, it does matter here. Since the central city populations tend to be the big users of public transportation and those populations are sometimes much smaller than the overall populations, the emissions that we credit to those people can be reasonably high. For example, in the case of New York City, more than one-third of the gains in reducing car-related emissions that are associated with central city residents are offset by higher emissions from public transit.

In the third column of Table 5, we turn to heating-related emissions. In this case, there is considerable heterogeneity across metropolitan areas. In New York, central city residents emit more than 5600 lb of carbon dioxide less than suburbanites. In Detroit, central city residents emit more than 6000 lb of carbon dioxide more than suburbanites.

The fourth column in Table 5 shows our result for electricity emissions. This column multiplies the NERC factor with the electricity usage gap. Almost everywhere, smaller urban homes mean lower electricity usage. Suburban electricity usage is lower in five cases when we consider average homes and in eight cases when

Table 6
Regression table.

	(1) City-suburb difference in emissions from driving	(2) City-suburb difference in emissions from public transportation	(3) City-suburb difference in emissions from home heating	(4) City-suburb difference in electricity	(5) City-suburb difference in carbon dioxide total emissions
Log(income)	4190 (2098)	−1894 (924)	4641 (2732)	9532 (2547)	16,468 (4557)
Log(population)	665 (394)	−478 (174)	1070 (514)	−876 (479)	381 (857)
Share of MSA employment within 5 miles of the city center	3068 (2623)	−1911 (1155)	12,772 (3415)	−2792 (3184)	11,137 (5697)
January mean temperature	−59 (20)	17 (9)	53 (26)	−61 (24)	−50 (43)
July mean temperature	93 (38)	−7 (17)	−22 (50)	158 (47)	222 (83)
Constant	−57,430 (21,624)	27,215 (9526)	−69,873 (28,159)	−98,891 (26,251)	−198,979 (46,972)
Number of observations	48	48	48	48	48
R^2	0.37	0.44	0.36	0.39	0.37

Notes: (1) Dependent variables are the suburb-city difference of total pounds of CO_2 emissions from the listed source. See Table 5. (2) The unit of analysis is a metropolitan area. (3) Standard errors are reported in parentheses. (4) Data is from the Integrated Public Use Microdata Series from the 2000 Census, the 2001 National Household Transportation Survey (NHTS), the Department of Energy, the National Transit Database, the 2001 Residential Energy Consumption Survey (RECS), the Environmental Protection Agency's Emissions and Generation Resource Integrated Database (eGRTD), and the National Oceanic and Atmospheric Administration.

we look at newer homes. Central city electricity usage does not always decline when we focus on newer homes, because while those homes may be more efficient, they are also more likely to have air conditioning.

The fifth column of Table 5 combines the results to show the total emissions gap between central cities and suburbs by metropolitan area. The sixth columns multiply this quantity by 43 dollars to find the total emissions cost, which ranges from −77 dollars, in Detroit, to 289 dollars, in New York. New York has the biggest gap between central city and suburbs. There are only two areas where suburbs have lower emissions than central cities. The seventh column shows the standard errors of the difference in costs which are again fairly small.

Table 6 regresses these differences on the same urban characteristics that we used in Table 4 to explain cross area differences in total carbon dioxide emissions. The dependent variable is the difference in driving emissions between the suburbs and the central city. The first regression shows that in bigger cities, suburbanites are more likely to drive longer distances relative to central city residents. The suburb-central city driving gap also gets larger in places with warm Julys and shorter in places with warm Januarys.

The second regression shows that the impact of population on emissions is reversed when we look at public transit. In this case, big city residence is particularly likely to be associated with high levels of public transit emissions, which is, after all, what we saw in New York City in Table 5. In richer cities, the gap also increases.

In the third regression, we see that the heating gap between central cities and suburbs is larger for bigger, richer and more centralized cities. Interestingly, there is no connection between temperature and the city-suburb heating gap. The fourth regression shows that temperature and income, but not city population or centralization, predict the difference in electricity emissions.

The fifth regression looks at the correlates of the total suburb-city emissions gap. The gap is larger in cities with more income and more people. It is also larger when January temperatures are high and when July temperatures are high.

5. Conclusion

Past research has investigated how national and regional greenhouse gas emissions vary as a function of the scale of population and income (Holtz-Eakin and Selden, 1995; Auffhammer and Carson, 2008). This paper has documented that holding population and income constant, that the spatial distribution of the population is also an important determinant of greenhouse gas production. If the urban population lived at higher population density levels closer to city centers in regions of the country with warmer winters and cooler summers in areas whose electric utilities used less coal for producing power, then household greenhouse gas production would be lower.

If carbon dioxide emissions are taxed appropriately, then individuals will make appropriate decisions about their locations without any further government interventions. However, if we believe that current carbon taxes, which are essentially zero, do not charge people for the full use of their energy consumption, then location decisions will fail to internalize environmental costs. In this paper, we have quantified the greenhouse gas externality that a standardized household would create if it were located in one of 66 major metropolitan areas and if it were located in the center city or suburb of 48 major metropolitan areas.

We estimate that costs per household range from $1150 dollars per year in San Diego to almost $2015 dollars per year in Memphis. Across areas, emissions are positively associated with July temperature, negatively associated with January temperature, and negatively associated with both city population and centralization. New York has the biggest suburban minus central city gap of 289 dollars.

Our work has many limitations. To translate our quantity estimates into dollar cost estimates, we have relied on the index weight of $43 of damage per ton of carbon dioxide, and this number lies within a large confidence interval. Our estimates are based on regressions that can provide only a very imperfect estimate of gasoline usage or electricity consumption in particular areas. We restricted ourselves to household energy use. Future research should also attempt to measure the household footprint associated with water use. Significant amounts of energy are used to supply water to these arid cities such as Los Angeles.

That being said, this paper does provide what we consider to be reasonable estimates of the emissions-related externalities associated with homes built in different areas. However, we would be skeptical about actually using these numbers as the basis for a tax on development in Oklahoma or a subsidy for development in San Diego. There are surely much better ways, like a direct carbon tax, to get people to internalize the social costs of their actions.

An optimal land use policy that imposed charges on new construction to internalize the environmental externalities from carbon emissions would impose higher taxes on high emissions areas. Yet land use regulations, which are thought by many to impose costs on local development, seem to be lower in places that have higher emissions. It is certainly possible that land-use restrictions are actually pushing people away from lower emission areas into higher emission areas. This topic seems to merit future research.

Acknowledgments

Glaeser thanks the Taubman Center for State and Local Government, the Rappaport Institute for Greater Boston and the Manhattan Institute. Kahn thanks the Richard S. Ziman Center for Real Estate at UCLA. Kristina Tobio and Ryan Vaughn provided excellent research assistance. We thank Stuart Rosenthal (the editor) and two reviewers for useful comments.

Appendix A. Calculating the prediction's standard errors

If we estimate a regression of the form $Y = X'\beta + \varepsilon$, then by Slutsky's Theorem and the Law of Large Numbers (LLN) the resulting coefficients will converge to a normally distributed random variable as follows:

$$\hat{\beta} \rightarrow^d N\left(\beta, \sigma_\beta^2\right)$$

where σ_β^2 is an appropriately defined standard error.

Note that in general the resulting predicted values may be written as

$$\widehat{Y} = \overline{X}'\hat{\beta}$$

where $\overline{X}$ is any $x \in \text{Support}(X)$. Therefore by a separate application of Slutsky's theorem $\widehat{Y}$ has the following asymptotic distribution:

$$\overline{X}'\hat{\beta} \rightarrow^d N\left(\overline{X}\beta, \overline{X}'\sigma_\beta^2\overline{X}\right)$$

Here we define

$$\overline{X}_i = \begin{pmatrix} \bar{x}_1 \\ \bar{x}_2 \\ x_{i3} \\ . \\ . \\ x_{ik} \end{pmatrix}$$

Further we collapse each estimated $\widehat{Y}$ by MSA. This is equivalent to multiplying each $\widehat{Y}$ by a vector γ'_{MSAj} where γ_{MSAj} contains $\frac{1}{n_j}$ for every observation in MSA "*j*", a 0 otherwise, and n_{jj} is the number of observations in MSA "*j*".

$$\gamma_{MSAj} := \begin{pmatrix} \frac{1}{n_j} \\ . \\ . \\ \frac{1}{n_j} \\ 0 \\ . \\ . \\ 0 \end{pmatrix}$$

Define $\overline{Y}_{MSAj} = \gamma'_{MSAj}\widehat{Y}$. By a third application of Slutsky's theorem the appropriate asymptotic distribution of $\overline{Y}_{MSAj}$ can be written as

$$\overline{Y}_{MSAj} \rightarrow^d N\left(\gamma'_{MSAj}\overline{X}\beta, \gamma'_{MSAj}\overline{X}'\sigma_\beta^2\overline{X}\gamma_{MSAj}\right)$$

Now define

$$\Omega := \gamma'_{MSAj}\overline{X}'\sigma_\beta^2\overline{X}\gamma_{MSAj}$$

and further define $C_{\overline{Y}_{MSAj}}$ to be an α confidence interval for $\overline{Y}_{MSAj}$.

$$C_{\overline{Y}_{MSAj}} = \left[\overline{Y}_{MSAj} - \left|\Omega^{-1/2}Z_\alpha\right|, \overline{Y}_{MSAj} + \left|\Omega^{-1/2}Z_\alpha\right|\right]$$
$$Z_\alpha := \Phi^{-1}(0.95)$$

Thus if we estimate Ω as

$$\widehat{\Omega} = \gamma'_{MSAj}X'\hat{\sigma}_\beta^2(\gamma'_{MSAj}X')$$

then we must only replace Z_α with its appropriate counterpart from the *t*-distribution.

Appendix B. Estimating energy consumption for renters and households living in multi-family housing

To estimate energy consumption for renters and owners in multi-family units for each of the 66 metropolitan areas, we adjust our metropolitan area specific predictions that were based on estimates of Eq. (2). For example, we estimated electricity consumption regressions based on Eq. (2) using Census IPUMS data for Los Angeles owners of single family homes. This yields a prediction of average electricity consumption for Los Angeles home owners of single family homes for a household with standardized demographics. We need to impute what this household's electricity consumption would have been if it had lived in Los Angeles as a renter of a single family home, an owner of a unit in a multi-family unit, or as a renter in a multi-family unit. To impute these last three categories, we use a second micro data set called the 2001 Residential Energy Consumption Survey (RECS).[31] This data set is a national sample with 4392 households that includes actual household energy consumption data. We use this energy consumption data to estimate national level OLS regressions; of the form:

$$\text{Log(energy consumption)} = \text{controls} + b_1 * \text{owner} + b_2 * \text{multi-family} + U$$

It is important to note that in estimating this national level regression using the RECS data, we include the same demographic controls (i.e. household age, income and household size) that we included in the IPUMS regressions. Controlling for these household demographics and division level dummies to control for climate conditions, we see to recover the percentage differences in energy consumption between owners of single family homes, renters of single family homes, owners in multi-family homes and renters who live in multi-family housing. Using the OLS estimates of b_1 and b_2 from these regressions, we adjust our metropolitan area specific predictions of energy consumption. For example, suppose that we estimate using the national data that b_2 equals zero and that b_1 equals .1. If based on our Los Angeles regression for owners of single family homes, we predict that the average home owner (with standardized demographics) consumes 9 MW h of electricity per year, then we would impute that the average renter consumes 8.18 MW h of electricity per year.[32]

This procedure allows us to predict a standardized household's consumption of energy for each metropolitan area, if it lived in four different housing categories (rental multi-family, owner multi-family, rental single family home, owner single family home). We then calculate a weighted average across these four categories by metropolitan area. The weights, which vary by metropolitan area, are based on the IPUMS data's frequency count of each of these four housing types. This multi-step method allows us to impute the energy consumption for renters and all residents in multi-family buildings, where we are concerned that reported energy expenditure does not accurately measure household consumption. Our correction procedure is especially important in a metropolitan area such as New York City, and is much less important in places like Houston where most of the households are single family owners.

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[31] http://www.eia.doe.gov/emeu/recs/recs2001/publicuse2001.html.

[32] The REX regressions are available on request.

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