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Energy footprint of the city: Effects of urban land use and transportation policies

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ABSTRACT

Urban land use and transportation policies have dramatic effects on the density and spatial distribution of residences in large cities. Effects of these policies have been analyzed using numerical urban simulation models. At the same time, the US Energy Information Administration's Residential Energy Consumption Survey has allowed researchers to investigate the relation between household energy consumption and characteristics of housing units.

This paper links these two lines of inquiry by demonstrating how simulation results on the implications of land use and transportation policies for the spatial form of cities can be used to compute implications for energy consumption. The resulting Urban Energy Footprint Model, "UEFM," allows one to trace the implications of a change in land use zoning or transportation policy through its effects on housing markets and residential location to the resulting changes in energy use for residential and commuting purposes – i.e. to understand the energy footprint of transportation, housing, and land use policies. Accordingly, the UEFM provides, perhaps for the first time, a link between urban and energy economics, and can allow measurement of rebound effects of energy policies in a more general equilibrium context.

1. Introduction

There is substantial interest in understanding and controlling the use of energy in the residential and transportation sectors of the US economy. Recent studies have attempted to measure energy consumption and/or carbon footprints for residents of cities around the world. Substantial differences in energy use across cities have been reported. For example, independent studies estimated the carbon footprint per capita for Washington, DC to be from 2.1 to 2.8 times that of New York City.[1] The most obvious difference between these two cities is the land use policies regulating the density of real estate development.[2] This suggests that urban land use and transportation policies may have a significant influence on the carbon footprint of the city. Few empirical studies have investigated the relation between patterns of urban development and energy use. Recently, Brownstone and Golob (2009) have shown that residential density is inversely related to vehicle energy consumption and Glaeser and Kahn (2010) report that older, denser cities have lower carbon dioxide emissions. Research on this topic has been limited by the lack of a model relating urban planning and development policies to energy use in cities. The urban energy footprint model (UEFM) developed in this paper is designed to fill that intellectual gap.

Ever since their introduction by Muth (1975), numerical urban simulation models have been used to project the effects of urban land use and transportation policies on spatial patterns of housing within cities.[3] Altmann and DeSalvo (1981) demonstrated that these models could replicate the spatial form and stylized facts characteristic of housing in moderate-sized US cities. Sullivan (1985) pioneered models in which employment was moved out of the central business district. Bertaud and Brueckner (2005) used a numerical urban simulation model to study the effects of planning policies, including the effects of limits on floor area ratios in cities. Bento et al. (2006) model the effects of some of the policies consid-

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[1] See Brown et al. (2008) and Dodman (2009) for sample estimates. There are many difficulties measuring total energy use and carbon emissions, but the reported differences between Washington and New York in both studies are larger than any likely measurement error. Note that both cities have well developed mass transit systems and simple statistical analysis of the cross-section of US cities in the first report ruled out the influence of climate or city size as the cause of differences in carbon footprint per capita.

[2] In addition to binding height and floor area ratio limits, significant portions of the District of Columbia have been declared historic. This limits both density and energy efficiency of the structures.

[3] For many purposes, it is possible to exclude housing supply and have urban land directly enter the household utility function. Many of the most important simulation models, particularly those dealing with optimal transportation investment in cities, have followed this "Mills and de Ferranti" approach and ignored housing supply. However, modeling the effects on energy use of a full range of housing and land use policies requires explicit consideration of the housing production function.

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ered here on urban sprawl using a similar model. Overall, there is a significant research tradition which "fits" numerical urban simulation models to cities and then traces the consequences of planning, land use, and transportation policies for the spatial pattern and density of development.

Given recent attention to issues of energy consumption, as well as rapid changes in the price of energy, research on the connection between urban form and energy consumption seems appropriate. The contribution of this paper is to make a formal connection between the outputs of a numerical urban simulation model and the consequences for energy consumption by residences and commuters. In order to make that connection, the UEFM includes features like multiple income groups, employment decentralized outside the CBD, and endogenous commuting congestion that have not been combined in previous urban simulation models. Incorporating highway congestion is crucial because it affects fuel consumption. Generating the energy cost of commuting as a function of vehicle velocity and distance traveled is relatively straightforward. Household energy consumption equations are obtained by estimating a model of residential energy consumption using the Residential Energy Consumption Survey.[4] Energy use in production, by the public sector, and in non-commuting trips is not considered in this model.

The next two sections of this paper briefly describe the numerical urban simulation model with two income groups and endogenous congestion in urban transportation. Then the residential energy consumption estimation is presented. Finally the model is simulated and the energy footprint implications of some stylized land use and energy policies are generated. The results indicate that the interaction between energy cost and the spatial form of the city is significant and should be considered when evaluating land use and energy initiatives.

2. The energy footprint urban simulation model

The basic form of the numerical simulation model follows the literature discussed above. It is calibrated to replicate the spatial housing pattern of a composite of five moderate-sized cities.[5] The household's utility function is assumed to be CES:

$$V = [\beta_1 y^\eta + \beta_2 h^\eta]^{1/\eta} \tag{1}$$

where h is housing consumption, and y represents all other goods, β_1 and β_2 are distribution parameters, and the constant elasticity of substitution between housing and all other goods is given by $1/(1-\eta)$. The household budget constraint is $I = y + rh + T$, where I is household income, T is the sum of both time and out-of-pocket commuting cost, r is the rental price of housing and h is the quantity of housing services consumed.[6] The price of y is normalized to unity. All other variables vary with distance from the edge of the central business district (CBD) where most employment is concentrated. There are two household types, low and high income. An iso-utility condition for each household type ensures that Muth's equation,

$$\frac{dr}{dk} = -\frac{dT}{dK}\frac{1}{h} \tag{2}$$

where k is distance from the center, holds.[7] Altmann and DeSalvo (1981) demonstrated that models with a single income group tend to generate cities that are too small and dense. To the extent that the UEFM is used for policy evaluation, effects on different income groups could be an attractive feature. For these reasons, households have been divided into low and high income groups.

Housing is produced by a perfectly competitive constant returns industry according to a CES production function:

$$H = [\alpha_1 S^\rho + \alpha_2 L^\rho]^{1/\rho} \tag{3}$$

where H is housing production, S and L are structure and land inputs, respectively, α_1 and α_2 are distribution parameters and the elasticity of substitution is $1/(1-\rho)$. As noted above, all this is common in the literature on simulation models which include explicit housing production.

All workers are either employed where they live or commute by automobile to the central business district.[8] A fixed proportion of land at each distance is used for highways. The road system is subject to congestion based on the number of workers commuting by automobile at any distance. Following Muth (1975) and Sullivan (1985), a version of what is commonly referred to as the Bureau of Public Roads congestion function is used in which commuting speed at a given location is inversely related to traffic volume according to:

$$v(k) = \frac{1}{a + bV(k)^c} \tag{4}$$

where $v(k)$ is the commuting speed at distance from the CBD, $V(k)$ is the traffic volume through location k, and a, b, and c are parameters that reflect the severity of the traffic congestion function. This particular formula is chosen to allow some level of flexibility in modeling the relation between commuting speed and traffic volume. As opposed to previous studies, the implications of vehicle velocity for time and out-of-pocket cost are considered separately because fuel efficiency and gasoline tax policies can change one without changing the other.

Most simulation models have all employment concentrated in a CBD. Sullivan (1985) has both a CBD and suburban business district. Because commuting distance is so important for energy use, the approach adopted is slightly different in that it follows McDonald (2009) in imposing on the city an exogenous employment density function of the form estimated by McMillen (2004). In a closed city model, total employment is always exogenous but assumption of a constant employment density function means that the location of firms does not respond to changes in the spatial distribution of households.[9] Overall, the UEFM closely resembles in the literature, particularly those models, like McDonald (2009) and Altmann and DeSalvo (1981), where the goal is to replicate the spatial pattern of housing density in actual cities. This density replication is important for understanding the energy footprint of cities because household energy use is very sensitive to structure type, i.e, single family detached versus multifamily, etc., as discussed in the next section on calibration. A more detailed discussion of the distinctive features of the UEFM and its solution is given in Appendix A.

The model is solved by imposing three fundamental equilibrium or no arbitrage conditions. First, for both low and high income households, utility must be equal at any location where they live

[4] US Department of Energy, Energy Information Agency, collects these data in a survey of households and utilities taken every four years. This paper relies on the 2005 data set which is the most recent survey available.

[5] The five cities are Charlotte, Kansas City, Denver, San Antonio, and Sacramento. These cities are similar in size and commuting times but differ in climate.

[6] There is one worker per household who must commute to work 5 days per week and work 8 h per day. Commuting time is deducted from leisure and valued at 40% of the wage rate, following guidelines stated in US Department of Transportation (2009). This follows the general convention in the urban simulation model literature.

[7] In the model calibration, the lower income households live closer to the city center. Muth's equation holds within the areas occupied by each income group. House prices and land rent are continuous functions but structure size is discontinuous at the boundary between income groups.

[8] If this model were applied to a city with significant mass transit, particularly a fixed rail system, some commuters could easily be allocated to that system using a modal choice model but it would also be necessary to estimate the energy used by this alternative mode.

[9] Thurston and Yezer (1994) provide empirical evidence that this is a good assumption for all major employment sectors except retail and services.

and lower at any location where they do not live. Second, households working outside the CBD receive a wage that is reduced by the amount of commuting cost for their household type so that they are indifferent between working locally and commuting. As Wheaton (2004) demonstrated in a series of papers, this is an implication of spatial labor market equilibrium. Finally land and housing prices adjust over space so that firms producing housing are in zero-profit equilibrium at all locations where they produce housing services, and profit is negative at locations outside the CBD where housing is not produced.

There is no explicit solution to the system of non-linear differential equations describing the transportation cost and housing density functions due to the complexity introduced by the presence of congestion. After some manipulation, the problem can be written as a system of simultaneous differential equations that can be solved using numerical methods. Once values for commuting costs and households are found, it is possible to solve recursively for all other variables in the model, such as the housing and land rental prices at all locations, by substituting the newly solved commuting cost at various distances into the closed city model.

3. Model calibration

Parameterization of the model closely follows the literature. The elasticity of substitution between structure and land inputs in the housing production function is generally estimated to be in the 0.5–1.0 range. The most common value used in simulation models is 0.75. For the CES utility function in Eq. (1), normalizing β_1 equal to 1, household utility maximization implies that:

$$\beta_2 = r\left[\frac{h}{1-T-rh}\right]^{1-\eta} \tag{5}$$

The distribution parameter of the household utility function, for each household type, can be imputed using data on housing consumption in five reference cities available from the American Housing Survey.

Following Muth (1975) and Altmann and DeSalvo's (1981) approach, the distribution parameters of the housing production function are computed using equations:

$$\alpha_1 = \frac{H^\rho}{\frac{L}{S}^{1-\rho}\frac{P_l}{P_s}L^\rho + S^\rho}$$

and

$$\alpha_2 = \alpha_1\frac{L}{S}^{1-\rho}\frac{P_l}{P_s}$$

where H, L, S, P_l, P_s are housing stock, lot size, structure inputs, rental price of land, and rental price of structure services respectively. Using American Housing Survey (AHS) data for the median housing unit in the five reference cities the two distribution parameters were determined to be $\alpha_1 = 1.1$ and $\alpha_2 = 0.09$.

One of the key parameters needed to close the model is the reservation land price at the edge of the city. The value adopted here was based on two factors. First, web-based searches for vacant land sales were used to find prices of buildable sites near the five reference cities. Second, house values for units on large, one acre or larger, lots at the edge of the cities were multiplied by a "rule of thumb" 15% land share. Both methods produced the value of approximately $8000 per acre used in the simulations.[10]

[10] This was capitalized at 6.5% to yield a $500 annual rental price. This calibration of housing production is also very similar to Bento et al. (2006) except that they place a $1000 rental price on land at the city edge.

The number of households was set at 550,000 implying 1.43 million in total population, based on average population characteristics of the five cities in the 2000 Census of Population.[11] The other parameters in the simulations follow those used in Bertaud and Brueckner (2005). Household income, I was set at $40,000 ($60,000) for the lower (higher) income households corresponding to the overall median of $50,000 for the five cities.[12] Estimated annual commuting cost per mile for each household includes both pecuniary and time costs of commuting. Pecuniary cost is equal to depreciation consistent with the Internal Revenue Service vehicle depreciation deduction per mile, plus the fuel cost. Following Bertaud and Brueckner (2005), time costs are equal to 40% of the commuter's wage. Following Muth (1975) and others the fraction of land used for housing is set at 1/4.[13]

Forty percent of total employment is concentrated in a CBD whose radius is 1 mile. The remaining employment is distributed over the area outside the CBD following an employment density function based on McMillen's (2004) estimates. Employment density is 87,500 per square mile in the CBD, falls to 11,000 per square mile at the edge of the CBD, and equals zero at a distance where total employment has been exhausted.

The outputs of the UEFM must be adapted to reflect the determinants of household energy use. Two sources of information on the relation between housing unit characteristics and energy consumption were used to connect the spatial structure of the housing market with energy use. The first was the Housing Assistance Supply Experiment (HASE) which was conducted to determine what factors influence household energy consumption. Neels (1982) analyzed the experimental data and concluded that changing the structure type from single family detached to multifamily lowers energy use by 20–50%, compared to 5–10% reductions from alterations due to energy efficiency upgrades of a given structure type and 2–5% from changes in occupant behavior due to variation in price structures.[14]

The second source of information on the relation between housing type and energy use is estimates from household energy consumption equations. These equations, reported later in this paper, are based on data from the 2005 Residential Energy Consumption Survey (RECS). Consistent with the HASE conclusions, these equations also reveal the importance of structure type and density along with square feet of interior space per unit as determinants of energy use.

Given these determinants of energy use in housing, the UEFM is designed to generate interior space per unit and allocate residential land among structure types, i.e. model the decision to supply single family detached versus attached versus multi-family units. This level of detail on housing characteristics has not been required in previous simulation models.[15] Structure type is modeled as a function of the density of housing services, measured as the floor–area ratio (FAR), square feet of interior space over land area. The FAR for individual structures was computed using AHS data for the

[11] An average household contains 2.6 persons in recent US census (2000).

[12] The 20% difference in income produces a distinctive jump in housing consumption at the border between low and high income households. In the five cities, median income in the area classified as "center city" in the AHS is $49,000 while that in the area classified as "suburbs" is $78,562.

[13] This is the fraction of gross area that is allocated to housing. Gross land area includes streets, non-residential uses, unbuildable land, etc.

[14] Most emphasis in current debates over energy use has been on improved energy efficiency or occupant behavior. However, the results from the Household Assistance Supply Experiment considered these adjustments and concluded that structure type and density, the factors generated from the UEFM, are or primary importance in determining household energy use.

[15] Many urban simulation models express the demand for housing in terms of interior space and generate housing supply in terms of square feet of interior space per square foot of land but previous models have not found it necessary to consider structure type.

Table 1
Calibration of the urban energy footprint model.

	Actual		Simulated	
	Avg. value	Value at edge of city[a]	Avg. value	Value at edge of city
Lot size (acre) – occupied units[b]	0.29	0.78	0.14	0.78
Unit (square feet) – occupied units[b]	1690	2345	1738	2263
Area (square miles)[c]	459		354	
Radius (assuming circle)[c]	12.1	10.6		
Median income[c]	49,050	78,562	50,000	60,000
Total occupied units[c]	549,703		550,000	
Time to work[c]	23.5	29.5	22.9	29.3
Fraction housed in 1 unit structures[c]	69%	100%	67%	100%
Fraction housed in 2–4 unit structures[c]	13%	0%	12%	0%
Fraction housed in 5+ unit structures[c]	17%	0%	21%	0%
Energy consumed in dwelling, per capita (mmBTUs)[d]	85.3	108.6	91.5	112.1

[a] Edge of city defined as households in the AHS with lot sizes between 0.5 and 2 acres.
[b] Source for actual values: AHS (2004).
[c] Source for actual values: ACS (2005).
[d] Source for actual values: RECS (2005).

reference cities. A linear probability model relating structure type and FAR was used to set the critical FAR values at which structure type changed.[16] The critical values of FAR were single family detached $FAR[0,1]$, single family attached $FAR(1,1.25]$, 2–4 unit multifamily $FAR(1.25,1.5]$ and multifamily with five or more units $FAR > 1.5$.

Table 1 compares results of the baseline UEFM simulation to the mean of actual measures available for the reference cities. Overall, the agreement between the baseline simulation and the actual means for the reference cities is quite close. Where there are differences, they may be due to problems in measuring the actual values. For example, the average lot size for the reference cities is based on the subset of AHS observations for which lot size was not missing. However, it is apparent that lot size is not missing at random. It is more likely to be missing for higher density units. Accordingly the smaller simulated value for lot size is to be expected.[17] The actual commuting time from the city edge is the mean commuting time in the suburbs which is, understandably, considerably less than the simulated time from the city boundary. The more compact market radius for the simulated city is also a standard aspect of simulation models even with multiple income groups.

The agreement between the actual and estimated distribution of structure types in Table 1 is gratifying and serves as additional validation for the methods used to transform simulated FAR into structure types. The final row shows the agreement between average energy consumption in the household and the simulated values. The method for transforming the outputs of the simulation model into estimates of energy consumption in the unit is discussed in the next section. The relation between actual average measures and simulated values is presented in the calibration section to illustrate that the model produces a distribution of housing sizes and structure types that, when transformed into energy use levels, agrees well with actual estimates of utilization. Given the focus of the simulation on energy consequences of urban development, this is the most crucial element of the calibration. In the final section on results, further validation of the UEFM is provided by its ability to replicate the effects of gasoline price shocks on housing densities that has been reported in a recent paper completed after the simulation results were generated.

[16] Unfortunately AHS-based measures of FAR appear to have substantial measurement error. Accordingly the statistical effort was supplemented by actual inspection of structure types using "Google Earth" in order to verify, for a random sample of properties, that visually estimated FARs corresponded to different structure types.

[17] Note that for suburban units, the problem of missing values is less important and the agreement of lot size is much better.

4. Household energy consumption equations

The UEFM requires estimation of total household energy consumption equations which relate household energy use to the housing characteristics generated by the urban simulation model.[18] Fortunately, this estimation requires only slight modification of the models used in the substantial literature on household demand for energy. There are some difficulties in estimating household energy consumption at the micro-level. Relaxing the assumption of a classic single-equation demand model, Dubin and McFadden (1984) treat appliance choice as endogenous, and Nesbakken (1999) treats housing consumption and energy technology choice as jointly determined endogenous variables. More recently, Reiss and White (2005) have considered the econometric implications of nonlinear energy price schedules. These developments in the literature have been designed to produce estimates of household energy demand equations that treat interior space as endogenous while the choice of location and house type is exogenous. Choice of residential location and house type is crucial to the UEFM simulation which only requires estimates of the relation between energy use and variation in structure type and size along with the effects of household income. In the UEFM, energy prices do not influence housing demand, except insofar as they change commuting costs and household location.

Given that the purpose here is to provide energy use equations for the UEFM, a single equation energy demand model is estimated.[19] The baseline specification is

$$lnE_i = \alpha + \beta lnA_i + \phi lnI_i + \delta lnp_i + S_i'\gamma + X_i'\varphi + \varepsilon_i \quad (6)$$

where E is energy consumption of household i, A is the area of interior space in the dwelling, I is income, p is the average price paid per thousand British thermal units (BTUs), S is a vector of variables describing the structure type, and X is a vector of other controls

[18] Household energy uses include heating, cooling, cooking, cleaning, television, computing, etc. The Residential Energy Survey records total energy use, including electricity, natural gas, heating oil, etc. Many of these energy uses are related to consumer durables in the unit. In the simulation, the implicit assumption is that consumer durables in the unit increase with interior space.

[19] This use of ordinary least squares to estimate energy demand functions with Residential Energy Survey Data follows the recent example of Ewing and Rong (2008). Alternative estimates designed to produce unconditional estimates of the electricity demand model were also implemented but, given the focus on effects of unit size and structure needed for the EFM, the results reported in Table 1 were judged to be the most robust. Glaeser and Kahn (2010) also use least squares estimates of an energy use equation in their work on greenness of cities.

Table 2
Estimating residential energy demand.

Control set	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent variable: household energy demand (log BTUs)						
	Empty	Climate	Energy technology	Household characteristics	Management	Other structure	Full controls
Total square feet of interior space (log)	0.257***	0.230***	0.232***	0.232***	0.270***	0.191***	0.152***
	[0.0184]	[0.0182]	[0.0173]	[0.0183]	[0.0185]	[0.0197]	[0.0181]
2–4 unit structure	−0.0599**	−0.0700**	−0.0746***	−0.0344	−0.0683**	−0.00947	−0.0338
	[0.0291]	[0.0285]	[0.0276]	[0.0289]	[0.0294]	[0.0271]	[0.0276]
5+ unit structure	−0.318***	−0.334***	−0.310***	−0.254***	−0.369***	−0.187***	−0.216***
	[0.0304]	[0.0303]	[0.0287]	[0.0327]	[0.0342]	[0.0327]	[0.0368]
Income (log)	0.0729***	0.0867***	0.0683***	0.0507***	0.0828***	0.0698***	0.0572***
	[0.0131]	[0.0128]	[0.0120]	[0.0128]	[0.0132]	[0.0128]	[0.0120]
Average price per BTU (log)	−0.930***	−0.870***	−0.743***	−0.944***	−0.896***	−0.906***	−0.763***
	[0.0294]	[0.0375]	[0.0335]	[0.0281]	[0.0298]	[0.0301]	[0.0388]
Natural gas available			0.270***				0.209***
			[0.0245]				[0.0236]
Fuel oil available			0.590***				0.513***
			[0.0284]				[0.0323]
Liquid petroleum gas available			0.377***				0.335***
			[0.0394]				[0.0385]
Kerosene available			−0.0656				−0.0626
			[0.127]				[0.105]
Cooling degree days (base 65, log)		0.114***					0.0920***
		[0.0117]					[0.0134]
Heating degree days (base 65, log)		0.114***					0.0695***
		[0.0129]					[0.0129]
Homeowner				0.0495*			0.0394
				[0.0275]			[0.0267]
Someone at home during weekdays				0.0265			0.0272
				[0.0195]			[0.0173]
Head of household works				−0.0359			−0.0283
				[0.0266]			[0.0239]
Number of household members				0.0874***			0.0822***
				[0.00721]			[0.00670]
Age of head of household				0.000449			−8.63e-05
				[0.000664]			[0.000600]
Paid energy bills directly					−0.198***		−0.108***
					[0.0341]		[0.0301]
Received energy assistance					0.119**		0.0710
					[0.0516]		[0.0439]
Member of condo association					−0.0791		0.0150
					[0.0486]		[0.0448]
Housing project					−0.119*		−0.102*
					[0.0612]		[0.0531]
Age of unit (log)						0.0687***	0.0340***
						[0.0110]	[0.0100]
Studio						−0.0648	−0.0397
						[0.0739]	[0.0650]
Number of windows						0.00972***	0.00665***
						[0.00117]	[0.00104]
Air conditioning						0.210***	0.149***
						[0.0287]	[0.0299]
High ceilings						0.0297	0.0192
						[0.0213]	[0.0187]
Constant	4.978***	3.551***	5.709***	5.066***	5.094***	4.823***	4.551***
	[0.202]	[0.251]	[0.201]	[0.199]	[0.209]	[0.208]	[0.258]
Observations	3066	3066	3066	3066	3066	3066	3066
R-squared	0.501	0.528	0.569	0.540	0.512	0.539	0.647

Robust standard errors in brackets.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

such as heating and cooling degree days that are commonly used in the literature.

Eq. (6) was estimated using data from the 2005 RECS dataset produced by the US Department of Energy's Energy Information Administration. The RECS includes detailed energy consumption, energy price, climate, structure, and household information, making it ideal for use in estimating parameters necessary for the UEFM. The RECS is based on probability-weighted household surveys conducted by interview for households and by mail questionnaire for energy suppliers.

The estimation results presented in Table 2 agree well with expectations and with previous estimates using earlier versions of the RECS. Of the variables crucial to the UEFM, structure type is very influential along with interior square feet. The income elasticity is small, but the income variable is mapped from a categorical variable so the estimate is attenuated.

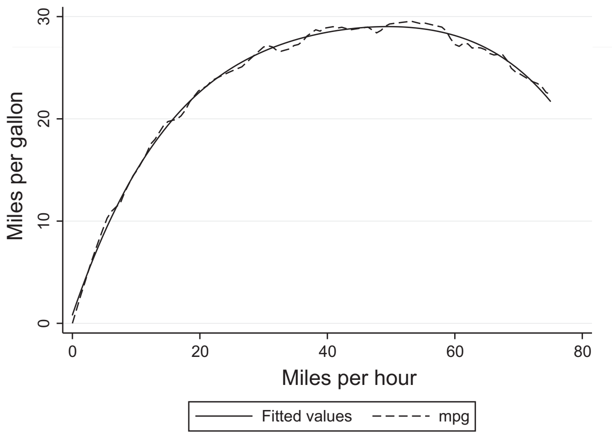

Fig. 1. Velocity-fuel efficiency relation.

5. Vehicle energy consumption equations

All households that commute are constrained to use vehicles whose energy consumption characteristics are identical. Nevertheless, because the UEFM has endogenous congestion that causes vehicle velocity to vary, energy consumption per mile traveled can vary significantly.

West et al. (1999) conducted an automobile fuel efficiency study at the Fuels, Engines, and Emissions Research Center at the Oak Ridge National Laboratory. The study provides data on the performance of a weighted average of the vehicles tested. These data are used to parameterize the relationship between velocity and gasoline consumption for a representative vehicle in a simulated city. The equation estimated is a fourth degree polynomial in velocity:

$$mpg_i = a + \sum_{j=1}^{4} \beta_j v_i^j + e_i \tag{7}$$

where *mpg* is miles per gallon, v is velocity and the βs are parameters to be estimated. The parameter estimates of Eq. (7) are used in the UEFM to simulate gasoline consumption as a function of vehicle velocity when traveling through a particular section of the city. The fuel efficiency function is based on gasoline with 100% petroleum content.[20] Peak fuel efficiency in miles per gallon is reached at about 40 miles per hour. This is below vehicle velocity in the outer suburbs but far greater that speeds in inner city congestion.[21] Fig. 1 displays the data from West et al. (1999) and fitted values from the estimates of Eq. (7).

6. Energy footprint of the city: alternative scenarios

The relation between selected variables for the actual and simulated baseline cities was presented in Table 1 and discussed in the section on model calibration. It is also instructive to examine the general spatial distribution of households, housing, and commuting patterns generated by the simulation.

Fig. 2 contains a series of graphs from the baseline simulation illustrating the spatial relation between urban characteristics such as the rental price of land, rental price of housing services, and structure/land ratio, commuting velocity, etc., and distance. Overall, these graphs are typical of models in the literature and are consistent with the spatial profile of cities. As noted in the discussion of Table 1 above, the simulation fits the composite of the five cities quite well. Because there are two income groups, there is a discontinuity in the amount of interior space and lot size at the boundary between low and high income households. The congestion feature of the model slows vehicle velocity considerably as commuters approach the CBD.

The spatial energy consumption profiles demonstrate the effect of distance on energy consumption for households that are identical except for the difference in income at the boundary between groups. The household energy consumption function appears to be stepwise linear.[22] One discontinuity is produced at the transition from low to high income residents. Other discontinuities arise at each change in structure type, from high density multifamily units, down to single family detached housing. Between jumps, energy consumption increases with distance from the CBD because of increases in vehicle operating time and increasing interior space in the housing unit. Overall, the spatial pattern of energy consumption in these simulation results appears consistent with empirical observations reported by Brownstone and Golob (2009).

6.1. Effects of raising gasoline prices

Table 3 contains the results of a series of simulation experiments in which both the physical characteristics and energy footprint of the baseline city can be compared to alternatives generated by varying one parameter. The first policy scenario involves increasing the price per gallon of gasoline by \$2. This shock could come from petroleum markets or through a tax.[23] The city becomes much more compact, with the area falling 10.3%. There is a substantial 11.3%, increase in density of housing at the edge of the CBD, and structure types shift from detached units, whose share falls 6.7%, to multifamily units, whose share rises 6.3%.

The percentage reduction in utility of low income households is three times as large as that of higher income households. This may seem surprising given that high income households commute much further and hence consume far more gasoline. However, the income elasticity of demand for housing is 0.60, which means that the substantial rise in housing price lowers welfare of low income households relatively more than high income households.[24]

It is not surprising that energy consumed in commuting falls 7.5% as mean driving time to work declines by 5.9%. However, what is notable is that household energy use falls by 2.0% as structure density rises and size falls. Furthermore, because household energy use is approximately seven times commuting energy use, the energy savings from the rise in gasoline prices in the household sector are 2.0 times as large as those from commuting. Gasoline taxes save more energy in the household sector due to the housing market response to more expensive commuting than in transporting commuters to work. The overall 2.6% fall in energy consumption is substantial. This does not include any increases in average

[20] Throughout this paper the fuel used by automobiles is assumed to be petroleum-based gasoline with 125,000 BTUs per gallon as opposed to 87,000 BTUs per gallon for ethanol.

[21] The estimated parameters reflect a fuel efficiency function for a gasoline-powered car, not a hybrid-electric. A hybrid powertrain would have much higher fuel efficiency at low speeds. Fuel consumption is based on continuous travel through a given annulus, and does not consider the effects of starting and stopping experienced when traveling on local city streets.

[22] The function appears to be a step function but the linear segments are actually positively sloped due to the effect of increasing interior space on energy use.

[23] It is assumed in this case that such a tax is fully passed onto consumers. We also do not rebate the tax proceeds to households as a lump sum transfer.

[24] While early estimates of the income elasticity of demand for housing using aggregate data were close to unity, over time estimates have fallen substantially. For example, Ioannides and Zabel (2008) estimate the elasticity to be just above 0.2 and Glaeser et al. (2008) suggest 0.25. In contrast, Guerrieri et al. (2010) report a value of 0.72. The value of 0.60 used here is essentially a compromise given the substantial diversity in the literature. See the discussion in Kim et al. (2009).

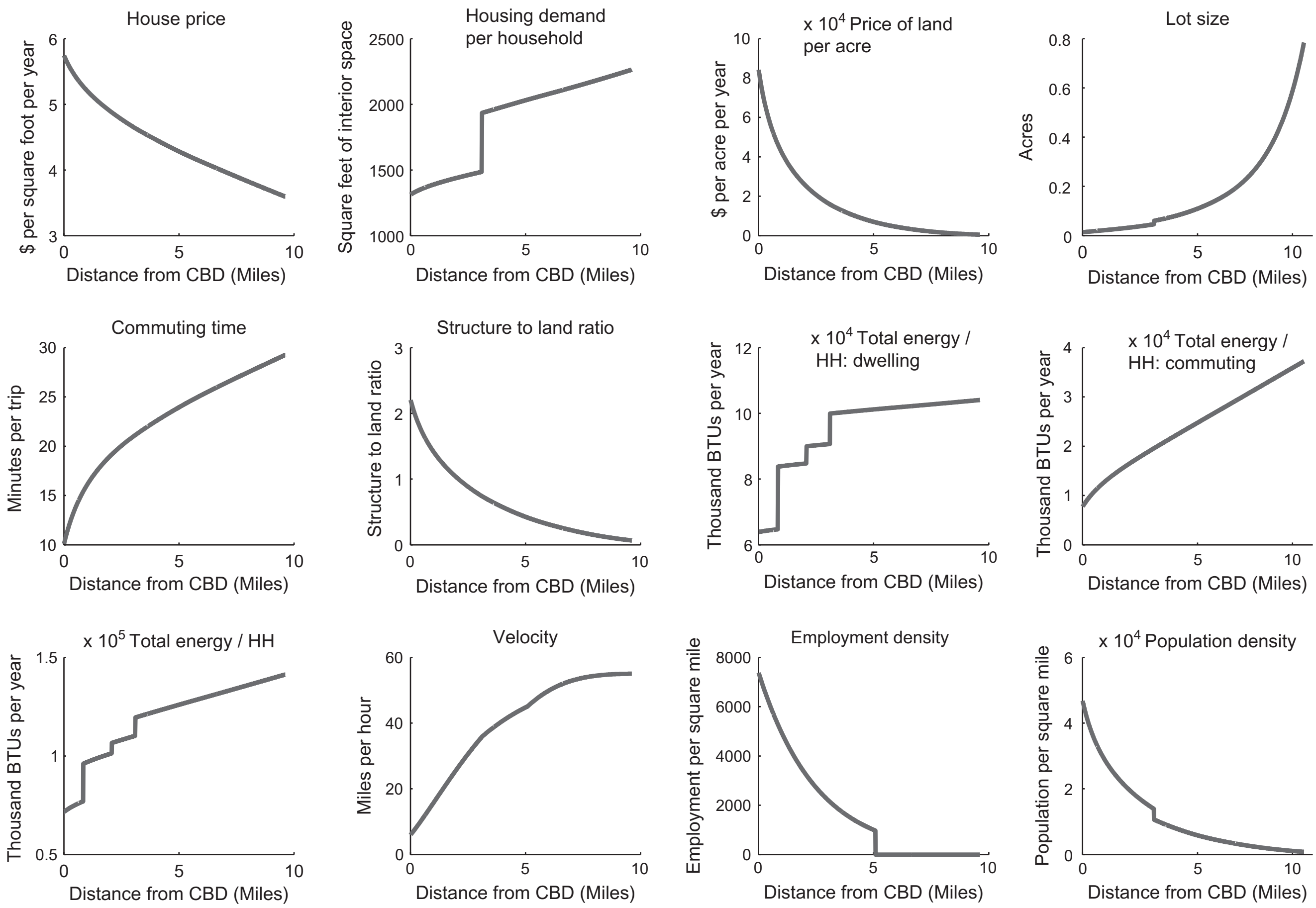

Fig. 2. Baseline city simulation.

vehicle fuel efficiency that would be prompted by higher gasoline prices.

The gasoline price simulation also provides an opportunity for external validation of the UEFM. Subsequent to the generation of the results in this paper, Molloy and Shan (2010) completed estimates of the effect of gasoline price shocks on the rate of urban housing construction as a function of commuting distance. They find that, for a large panel of cities, positive gasoline price shocks depress the ratio of construction to housing stock when average commuting time in the area is in the 24–28 min time range.[25] The UEFM gasoline price shock simulation predicts that housing density falls at distances greater than 5 miles from the edge of the CBD. At this distance, commuting time to the CBD is 35 min which appears significantly greater than the Molloy and Shan finding. There are two reasons why Molloy and Shan's estimates of the commuting time at which gasoline price increases cause density to fall might differ from the UEFM. First, their results are for a large panel of US cities and the UEFM is calibrated to five mid-sized cities. Second, their result is based on average commuting time for all workers in the area and the UEFM reports commuting time to CBD employment. Fortunately there is a way to adjust for the difference in average commuting time and CBD commuting time. It is possible to observe the average commuting time for census tracts located 5 miles from the CBD for one of the cities used to calibrate the UEFM. This was done for Denver and the average commuting time for the tracts touched by a circle inscribed 5 miles outside the CBD was 28 min, which is consistent with the Molloy and Shan estimate of 24–28 min for the distance at which the construction/housing stock ratio falls in response to a positive housing price shock.

6.2. Effects of raising vehicle fuel efficiency

This scenario is based on the recently enacted rise in CAFE standards and assumes that the current fleet of automobiles is transformed into one that is 25% more fuel efficient. The standards raise the relation between velocity and miles per gallon by 25% at every speed.[26]

Increased fuel efficiency lowers the energy and pecuniary costs of commuting, but gives rise to rebound effects as the area of the city increases 2.1% and commuting times rise by 1.3%. Housing prices and structure density near the city center both fall and this causes a second hidden rebound effect as energy utilization rises due to lower density housing. The utility of lower income workers rises relatively more than that of higher income workers. This result may appear surprising because higher income households commute far longer distances but the fall in house prices primarily benefits lower income households.

The energy consumed by commuting falls 18.7%, but greater fuel efficiency has the indirect or rebound effect of increasing city size and interior space as it shifts households out of multi-family

[25] Molloy and Shan (2010) find that the effect of a gasoline price increase on construction/housing stock ratios at shorter commuting times is non-significant. Because the UEFM is a closed city model, population density reductions in outer areas automatically produces increases in density closer to the CBD.

[26] To the extent that fuel efficiency gains involve changes to hybrid technology, the relation between miles per gallon and velocity would rise more at low than at high velocities. This alternative could, of course, also be simulated and the differences among technologies of automobile propulsion could be explored.

Table 3
Baseline simulation and counterfactual scenarios.

Scenario description	[1] Baseline	[2] +$2 gasoline			[3] +25% fuel economy			[4] +10% income		
Variable			Δ	%Δ		Δ	%Δ		Δ	%Δ
Unit (square feet)	1738	1707	−30.7	−1.8	1744	6.3	0.4	1941	202.9	11.7
Lot size (acre) – detached units	0.141	0.137	−0.004	−2.5	0.142	0.001	0.5	0.157	0.016	11.5
Price of land per acre at edge of CBD ($k)	84.2	99.7	15.6	18.5	81.1	−3.0	−3.6	85.0	0.8	1.0
Aggregate land rent ($million)	444	462	17.4	3.9	441	−3.6	−0.8	496	51.1	11.5
Floor-area ratio at edge of CBD	2.20	2.45	0.25	11.3	2.15	−0.05	−2.3	2.22	0.01	0.6
Area (square miles)	354	318	−36.4	−10.3	362	7.4	2.1	396	41.9	11.8
Time to work	22.92	21.57	−1.35	−5.9	23.22	0.30	1.3	24.15	1.23	5.4
Utility of low-income households	16.20	15.89	−0.31	−1.9	16.26	0.06	0.4	18.16	1.96	12.1
Utility of high-income households	20.83	20.70	−0.13	−0.6	20.85	0.03	0.1	23.17	2.34	11.3
Fraction housed in 1 unit structures (%)	67.1	60.4	−6.7	−10.0	68.5	1.4	2.0	67.4	0.3	0.5
Fraction housed in 2–4 unit structures (%)	12.0	12.5	0.5	3.9	11.9	−0.1	−0.6	12.0	0.0	−0.2
Fraction housed in 5+ unit structures (%)	20.9	27.2	6.3	30.0	19.6	−1.3	−6.2	20.6	−0.3	−1.4
Energy consumed while commuting*,**	6.62	6.12	−0.50	−7.5	5.38	−1.24	−18.7	7.08	0.45	6.9
Energy consumed in dwelling*	50.35	49.36	−0.99	−2.0	50.55	0.20	0.4	52.18	1.83	3.6
Energy consumed, total*	56.97	55.48	−1.49	−2.6	55.93	−1.04	−1.8	59.26	2.28	4.0

Scenario description	[1] Baseline	[5] 5% of land to housing 5% now open space			[6] Greenbelt at 9 miles from city-center			[7] FAR maximum of 1.4			[8] Floor–area ratio restriction in suburbs***		
			Δ	%Δ		Δ	%Δ		Δ	%Δ		Δ	%Δ
Unit (square feet)	1738	1732	−5.7	−0.3	1713	−24.2	−1.4	1736	−1.6	−0.1	1725	−12.6	−0.7
Lot size (acre) – detached units	0.141	0.140	−0.001	−0.5	0.103	−0.038	−27.3	0.140	−0.001	−0.5	0.166	0.025	17.7
Price of land per acre at edge of CBD ($k)	84.2	87.7	3.5	4.2	87.6	3.5	4.1	89.1	4.9	5.8	87.3	3.1	3.7
Aggregate land rent ($million)	444	448	4.0	0.9	467	22.4	5.0	461	16.3	3.7	512	67.1	15.1
Floor-area ratio at edge of CBD	2.20	2.26	0.06	2.6	2.26	0.06	2.6	1.40	−0.80	−36.4	2.25	0.05	2.3
Area (square miles)	354	363	8.7	2.5	255	−99.3	−28.0	357	2.7	0.8	373	18.2	5.1
Time to work	22.92	23.12	0.20	0.9	22.03	−0.89	−3.9	23.84	0.91	4.0	22.56	−0.37	−1.6
Utility of low-income households	16.20	16.14	−0.06	−0.3	16.14	−0.06	−0.3	16.12	−0.08	−0.5	16.15	−0.05	−0.3
Utility of high-income households	20.83	20.80	−0.02	−0.1	20.75	−0.08	−0.4	20.79	−0.04	−0.2	20.81	−0.02	−0.1
Fraction housed in 1 unit structures (%)	67.1	65.5	−1.6	−2.4	63.1	−4.0	−5.9	67.7	0.6	0.8	63.4	−3.7	−5.5
Fraction housed in 2–4 unit structures (%)	12.0	12.2	0.2	1.9	13.3	1.3	10.8	12.4	0.4	3.0	13.2	1.2	10.3
Fraction housed in 5+ unit structures (%)	20.9	22.3	1.4	6.5	23.6	2.7	12.8	20.0	−0.9	−4.4	23.3	2.4	11.6
Energy consumed while commuting*,**	6.62	6.70	0.07	1.1	6.22	−0.40	−6.1	6.86	0.24	3.6	6.53	−0.09	−1.4
Energy consumed in dwelling*	50.35	50.15	−0.20	−0.4	49.90	−0.46	−0.9	51.63	1.28	2.5	49.97	−0.38	−0.7
Energy consumed, total*	56.97	56.84	−0.13	−0.2	56.11	−0.86	−1.5	58.49	1.52	2.7	56.50	−0.47	−0.8
Energy consumed while commuting*,**	12.44	12.63	0.18	1.5	12.08	−0.36	−2.9	13.52	1.08	8.7	11.97	−0.48	−3.8
Energy consumed in dwelling*	48.82	48.61	−0.22	−0.4	48.51	−0.31	−0.6	50.64	1.81	3.7	47.64	−1.18	−2.4
Energy consumed, total*	61.27	61.23	−0.04	−0.1	60.59	60.59	−1.1	64.16	2.89	4.7	59.61	−1.66	−2.7

* Trillion BTUs.
** Based on a conversion rate of 1 gallon – 125,000 btus.
*** When the optimal floor-area ratio is between 0.5 and 0.2, it is restricted to be 0.2.

housing units. The resulting increase in energy consumption by households is about 20% of the fall in energy used in commuting. The overall fall in energy consumption is 1.8%, which seems modest given the substantial 25% increase in fuel efficiency.

Some additional insight into the relation between energy policy and energy use in cities is gained by comparing the results of these two policy scenarios. Raising the fuel efficiency of automobiles has both direct and indirect effects on energy use. The direct effect is the fall in energy consumed based on the current commuting pattern. The indirect effect arises from the fall in cost per mile of commuting and is the sum of the rebound effects due to longer commutes and lower density housing. Unlike the higher CAFE standards, raising the price of gasoline has no direct effect but has indirect effects due to the fall in commuting distance and rise in housing density in response to higher cost per mile of commuting.

Table 4 facilitates comparison of the effects of changing gasoline prices and fuel efficiency by reporting the results of simulation experiments in which gasoline price falls (rises) 10% and one in which fuel efficiency rises (falls) 10%. In either case, the fuel cost per mile of travel falls (rises), holding vehicle velocity constant, by 10%. Changing fuel efficiency has a large and obvious direct effect equal to 10% of total energy use in commuting. The indirect or rebound effects of fuel efficiency are both significant. The indirect housing effect is approximately twice as large as the commuting rebound effect. Note that these indirect or rebound effects of

Table 4
Energy decomposition.

	Baseline	+10% gas price	−10% fuel economy	−10% gas price	+10% fuel economy
Commuting energy[a]	6621	6564	7221	6674	6067
Household energy[a]	50,351	50,231	50,231	50,448	50,448
Total[a]	56,972	56,795	57,452	57,122	56,515
Direct effect on commuting energy[a]			657		−607
Indirect effect on commuting energy[a]		−57	−57	53	53
Indirect effect on household energy[a]		−120	−120	97	97
Ratio of indirect effects on commuting/housing		47.2%	47.2%	54.3%	54.3%

[a] Billions of btus.

changing fuel efficiency are identical to those of changing gasoline price. Because these policies have income effects, the size of the indirect energy use effects of falling gasoline prices or rising fuel efficiency are slightly larger than the effects of rising gasoline prices. To the extent that, for policy purposes, one wanted to identify an energy cost of sprawl generated by falling transportation costs, these indirect costs provide a possible answer.

6.3. Effects of rising household income

Rising income is included as a policy variable in Table 3 to indicate the general effects of economic growth in cities on energy consumption for housing space and commuting. Obviously, energy consumption rises with income for many other reasons than commuting and household use because the energy component of other consumption goods and services is significant. The purpose here is to abstract from the general effects of rising income on energy consumption and focus entirely on the changes in energy use related to housing space, commuting, and the spatial structure of the city.

A 10% increase in income causes the city area to expand by 11.8% and commuting time to increase 4.6%. Housing prices rise and the density of structures at any given location increases. All of these changes are consistent with results produced by previous urban simulation models.

Energy consumption rises 3.6% in housing and 6.9% in commuting. Overall this implies a modest income elasticity of demand for energy use in housing and commuting. One reason for the modest increase in energy use is the low, 0.60, income elasticity of demand for housing and the saving in energy use associated with an increase in structure density.

6.4. Effects of increasing land for open space

The fourth scenario involves taking 5% of the land currently used for housing and using it for open space. This might appear to have a high energy cost because its direct effect is to increase the size of a closed city. However, the policy raises residential land prices. This has two effects on housing. First density of housing increases and there is more multifamily housing. Second, interior space per unit decreases. The net result is a modest, 2.5% increase in land area of the city but the additional energy used in commuting (only about 1.1%) is smaller than the fall in energy used in households. Overall, the UEFM produces the rather surprising result that the net effect of the full adjustment to the increase in land for open space is essentially energy neutral (actually a 0.2% fall). Because of their sensitivity to house price increases, the utility of lower income households falls more than higher income households but this ignores any benefits arising from the additional open space in the city.[27]

[27] Bento et al. (2006) show that is it possible to simulate a city where open space has an additive, independent effect on a Cobb–Douglas utility function.

6.5. Effects of a greenbelt

There is a significant literature on the greenbelt as a second best policy response to the failure to price urban highway congestion externalities, such as those generated endogenously by the UEFM.[28] The greenbelt is placed 9 miles from the city center, reducing the radius of the baseline city by 15% and the total area by 28%. The lot size of detached units falls by 27.3%. Effects on the city stem from the consequent rise in land and housing prices that increase the density of housing and move structure types toward multifamily. Because the greenbelt is located on land used for the lowest density housing in the city, the effects on housing supply, prices, and density of removing 6.1% of land used for housing at the edge of the city are smaller than for the previous case which removed 5% of land throughout the city available for urban housing.

The greenbelt is assumed to be sufficiently wide to deter "leap-frog" development outside the city. Energy use falls 6.1% in commuting and 0.9% in household uses. Once again, because household energy use is about seven times commuting use, the absolute amount of energy savings in each sector is approximately equal.

6.6. Effects of zoning that limits inner city housing density

Land use zoning and building codes can limit development of cities in several ways. Zoning that restricts the supply of housing in the inner city generally takes the form limits on the maximum height or floor area ratio (FAR). Bertaud and Brueckner (2005) have modeled the land use effects of this type of regulation and obtained results logically consistent with those in the UEFM except that they do not have endogenous congestion or energy use. The simulation exercise shown here involves FAR regulation in the inner city.

The specific zoning proposal in the simulation restricts inner city FAR to a maximum of 1.4. This is substantially below the 2.2 FAR at the CBD boundary in the baseline simulation. For the baseline case, the FAR falls to 1.7 at a distance of 0.85 miles from the CBD. In the presence of FAR regulation, the FAR reaches 1.4 at 1.1 miles. Accordingly, the regulation raises house prices, particularly to lower income households and has the greatest proportional effect on their utility. The land area occupied by multifamily structures with 5+ units increases as the radius of multifamily development rises 13%. However the average density of these multifamily units is reduced so much that total multifamily units decline slightly in spite of the increase in land used for multifamily development.

The effects on housing are very similar to those reported in Bertaud and Brueckner (2005) as the area occupied by higher density housing increases but the fraction of households in these units falls. The net result is a substantial 2.7% increase in household energy consumption. There is a very large 4.0% increase in commut-

[28] Brueckner et al. (2001) have demonstrated the effects of greenbelts in an urban simulation model and Brueckner and Helsley (2011) have demonstrated the second best welfare effects of greenbelts in the presence of unpriced highway congestion.

ing time and energy use in commuting increases 3.6%. This zoning policy increases energy use in both commuting and housing but the effects on the household sector are five times those from increased commuting.

6.7. Effects of suburban limits on housing density

Regulations that limit suburban housing density often take the form of minimum lot zoning. This is simulated in the UEFM by controlling the maximum FAR in suburban areas. Specifically, all areas for which the FAR in the baseline simulation fell between 0.5 and 0.2, i.e. areas that would ordinarily be developed as single family detached housing, are restricted to a maximum FAR of 0.2. This effectively lowers housing densities in an outer suburban ring in a manner isomorphic to implementing minimum lot zoning. The lot size of detached units rises by 17.7%. There is a corresponding increase of 5.1% in the city area. This contrasts with the 0.8% increase in land area due to the previous case of inner city density regulation where suburban densities could rise in response to higher house prices. The effects on relative utilities of low and high income households of minimum lot zoning are dramatically different than was the case for a greenbelt. While utilities of both groups fall in either case, relatively speaking minimum lot zoning has a far larger effect on low than high income households. This may explain why minimum lot zoning is more attractive than greenbelts among higher income suburban households.

Effects of minimum lot zoning on energy use may be the most counterintuitive result obtained from the UEFM. The direct effect of minimum lot zoning is to reduce residential densities and cause the outer suburban areas of the city to sprawl so that commuting distances from these suburbs to the CBD rise. How then can energy used in both households and commuting fall? The key is that minimum lot zoning is imposed in areas where single family housing would have been built in any event. Recall that structure type, single family detached versus others, has a major effect on household energy consumption and this is not changed by the zoning. The indirect effects of minimum lot zoning arise because it drives up the price of housing and this causes household densities in the unregulated inner parts of the city to rise significantly as households consume less space and live closer to the CBD. There is a substantial shift from the regulated single family sector, which drops 5.5%, to the unregulated higher density sectors which expand 10.3% and 11.6% respectively. While a few suburban households commute longer distances, most of the other households in the now more compact inner city commute shorter distances and the commuting time to work actually falls 1.6% and energy use in commuting falls 1.4%.

7. Conclusions

This paper was inspired by the empirical findings in Brown et al. (2008) and Glaeser and Kahn (2010), suggesting substantial differences in energy use and carbon footprint among US cities that are not explained by variation in climate or availability of mass transit. These differences suggest that fundamental characteristics of the urban development process have a profound influence on energy use in cities. However, the literature on the SUM has demonstrated that urban development is extremely complex and numerical urban simulation models are necessary to understand land use, commuting, and housing in cities with traffic congestion.

Currently, there is a tendency to evaluate energy policy proposals without considering feedback or rebound effects that work through the urban land market. At the same time, the energy implications of urban development policies are not well understood or considered when these policies are implemented. The UEFM can aid in the evaluation of energy and urban development policies, and particularly deal with unintended consequences of these efforts. The particular form of the urban simulation model developed for this task has endogenous congestion determining commuting costs and generates a spatial distribution of structure types so that crucial factors determining energy use could be studied.

Application of the UEFM has been illustrated by simulating of a series of scenarios in which a single aspect of the city changed. This was done to demonstrate operation of the model and facilitate discussion of its results. Clearly simulation of the effects of multiple policy changes is possible and perhaps even desirable in understanding differences in energy use across cities. Some forms of extra complexity, such as recognizing that hybrid automobiles have a different relation between velocity and miles per gallon could be easily accommodated by the model.

Even with relatively simple policy innovations illustrated here, the hypothesis that energy use in housing and transportation are critically linked has been validated and rather counterintuitive results have been obtained. One dramatic illustration of this linkage is the effects of gasoline price increases, which result in reductions in household energy use due to the indirect effects of housing prices on the size and density of units that are larger than energy savings due to shorter commuting trips. Another example is the policy of increasing energy efficiency of the automobile fleet. It is well known that increased fuel efficiency is partly offset by a "rebound" effect in which driving increases. However the UEFM simulations demonstrate that lower house prices cause increased unit size and lower structure densities that increase energy consumption by households. These types of indirect effects should not be neglected in energy policy evaluation. Perhaps the most counterintuitive result is the finding that there are significant energy savings from imposition of minimum lot zoning in the suburbs where the appearance of sprawl hides savings due to rising house prices and increased multi-family housing in areas where density is not restricted.

While this model has been calibrated and implemented for moderate size US cities, the methods are clearly applicable to cities around the world that exhibit the negative exponential density patterns characteristic of the SUM. Indeed, the fastest growing cities in the world, where decisions on transportation and land use are currently having the most profound effects on energy consumption are in China. Bi et al. (2011) report on the significant increases in carbon emissions in Nanjing, which is typical of Chinese cities. However, Ke et al. (2009) have shown, using a cross-sectional data set from 650 Chinese cities that spatial variation in density functions in these cities is quite similar to that found empirically in US cities. Accordingly, it may be that the UEFM can be adapted to Chinese cities, and other cities with similar density patterns, after a moderate adjustment in calibration.

Other versions of the numerical urban simulation model have potential for use in analysis of the energy implications of urban development. Models where residential investment is putty-clay rather than putty-putty in the case of the UEFM could certainly be valuable. For larger city sizes, commuting by an alternative mode, perhaps express bus or fixed rail, could be added to simulate effects of providing mass transit. This would require an understanding of energy use in mass transit and a model of modal choice by commuters. Another limitation of the current model is that the spatial distribution of employment is exogenous. In sum, the version of the UEFM presented here should be viewed as a first attempt to demonstrate what will hopefully become a standard method for evaluating energy and urban development policies.

Appendix A. Technical appendix: an urban simulation model with endogenous traffic congestion

As noted in the text above, the basic form of the numerical simulation model follows the literature. The UEFM shares many characteristics with other simulation models. For example, there is a CBD which contains no housing and a fixed amount of total city employment and the proportion of land used for housing, θ, is fixed throughout the residential portion of the city as is the proportion of land used for highways. However, the addition of multiple income groups, employment disbursed outside the CBD, endogenous highway congestion, and a nonlinear fuel consumption–speed relation distinguishes it from previous models. This appendix discusses these additional complexities of the UEFM and their implications for the approach used to solve the model.

A.1. Fundamental equilibrium conditions

The UEFM simulates a city by imposing three fundamental equilibrium or no arbitrage conditions.

1. No household can raise its utility by moving. For a household of type $i = \{High, Low\}$, utility must be equal at all locations where the household resides and it must be lower at any location where the household does not live. This iso-utility condition for households determines a spatial pattern of house prices, in which price declines with distance from the central business district at a rate sufficient to compensate for the cost of commuting, following Muth's equation, $dr/dk = -dT(k)/dk/h$, where k is the distance from the CBD, $T(k)$ is the commuting cost at distance k, r is the price of housing services and h is the quantity of housing consumed.
2. No household can raise its utility by changing its location of employment. This second no arbitrage condition requires that the local wage declines with distance from the CBD at a rate exactly equal to the saving in the commuting cost, so workers in the same skill group receive the same utility regardless whether they commute or work locally.
3. The third equilibrium condition is that housing producers earn normal profit at all locations where they produce housing and less than normal profit at all other locations.

The model closes on two conditions. First, at the city boundary, the land price falls to the agricultural reservation price. Second, all population in this closed city model is housed within the city boundary.

A.2. Non-CBD employment

As with previous urban simulation models, there is a CBD that contains no housing and provides employment for households in the city. In the UEFM, a fixed fraction of total city employment is located in this CBD, whereas in past simulations all employment is located in the CBD or in a combination of the CBD and a suburban employment zone. This change in the spatial distribution of employment allows the UEFM to approximate observed commuting patterns and times.

The spatial distribution of local employment, taken as exogenous in the UEFM, is determined by the employment density gradient. In the SUM the employment density gradient is modeled as a negative exponential, $D^E_L(k) = D^E_{CBD}e^{-\lambda k}$ where D^E_{CBD} is employment per unit land at the edge of the CBD and λ is the density gradient. Empirical employment density functions have been estimated in a number of papers. The function used here is based on McMillen (2004). The number of workers locally employed at distances greater than κ, $E_L(\kappa)$, can be written as:

$$E_L(\kappa) = E_T - E_{CBD}\int_0^{\kappa} D^E_{CBD}e^{-\lambda k}dk \tag{A.1}$$

where E_{CBD} is the predetermined employment in the CBD. It is convenient to normalize $k = 0$ at the edge of the CBD because all activity within the CBD is exogenous to the model.

A.3. Two income groups

Earlier versions of the UEFM had one group and produced very similar results. The introduction of a second income group increases the concavity of the housing density gradient, resulting in a city that has greater population density near the CBD and yet has extensive low-density suburbs. First it is necessary to determine which household type has the steeper bid rent curve for housing, based on Muth's equation. In the current model calibration, the income elasticity of demand, although rather low at 0.60, is sufficiently large so that it outweighs the wage effect on transportation costs in Muth's equation. Accordingly low income households have slightly steeper bid rent functions for housing and hence locate closer to the city center.[29] In the solution of the UEFM, the city is, in effect, simulated twice. The first simulation imposes the no-arbitrage conditions on low-income households and simulates the inner part of the city, i.e. the entire population of low income workers is housed first. Then the high-income portion of the city is simulated.

A.4. Endogenous highway congestion

Following an approach first developed by Muth (1975) but not used in other urban models, commuting speed at a given location is inversely related to the ratio of traffic volume to land used for roads, according to Eq. (3) above which is repeated here for expositional convenience:

$$v(k) = \frac{1}{a + bV(k)^c} \tag{A.2}$$

where $v(k)$ is the commuting speed at distance k from the CBD, $V(k)$ is the traffic volume through location k, and $H(k)$ is the surface area of land used for roads at location k. Traffic congestion varies inversely with distance because both commuting volume rises and road capacity falls as more and more commuters are packed onto less highway capacity near the CBD. The three parameters, a, b, and c, are set based on a well-developed literature on the relation between lane miles and travel speeds.[30] Final calibration of the baseline simulation is designed so that velocity falls from 45 miles per hour in the suburbs to 5 miles per hour in the CBD.

Because the UEFM is a closed city model in which the city population is held constant and all workers either commute to the city center (CBD) or work locally, the traffic volume passing through location k is equal to the difference between total employment in the city and the workers living within distance k, minus the total number of locally employed workers who reside beyond distance k, i.e.

$$V(k) = E_T - N(k) - E_L(k) \tag{A.3}$$

[29] Empirical observation of US cities indicates that household income increases with distance from the city center but that is not necessarily the case with cities around the world. There may be other reasons for the empirical correlation between income and distance in US cities. Brueckner and Rosenthal (2009) have argued that this stylized fact may also be due to a preference for new housing and may reverse in the future.

[30] Early calibration of the congestion function implied by (3) was done in Washington, DC by Boardman and Lave (1977). For a more recent treatment see Liu and McDonald (1998).

where E_T is total city employment, $N(k)$ is the number of workers housed within distance k and $E_L(k)$ is the total number of workers employed locally at distances greater than k and hence having no need to commute to work.

Commuting time from the edge of the CBD to distance κ is determined by the varying speed through each section of the trip so that total travel time to the CBD is: $t(\kappa) = \int_0^\kappa v(k)^{-1}dk$. Substituting the vehicle velocity function for $v(k)$ (based on Eqs. (A.1) and (A.2)), yields the specific commuting time function:

$$t(\kappa) = \int_{CBD}^{\kappa} a + b\left[\frac{E_T - N(k) - E_L(k)}{H(k)}\right]^c dk \tag{A.4}$$

A.5. Non-linear fuel consumption-speed relation

Gasoline utilization in commuting varies inversely with velocity according to an engineering process function represented by $g = G(v(k))$. Commuting costs from distance κ can be expressed in monetary terms as the sum of fixed cost including travel cost from the edge of the CBD to employment within the CBD noted m_0, costs strictly proportional to distance, $m_1\kappa$, gasoline consumption based on the product of gallons per mile and price per gallon, $p_g G(v(\kappa))^{-1}$, and the product of travel time and value of time which is set at half the wage rate for each income group, $w_i t(\kappa)/2$. Taken together, this means that total commuting cost is given by:

$$T(\kappa) = m_0 + m_1\kappa + p_g\int_{CBD}^{\kappa}\frac{1}{G(V(k))}dk + \frac{w_i}{2}\int_{CBD}^{\kappa}\frac{1}{v(k)}dk \tag{A.5}$$

The derivative of the commuting cost function plays a critical role in Muth's equation at the heart of the SUM. Defining the edge of the CBD as $k = 0$ and letting k_{CBD} equal the average commuting distance from the edge of the CBD to employment within the CBD, the marginal commuting cost function may be written as:

$$\frac{dT}{dk} = m_1 + \frac{p_g}{G(v(\kappa))} + \frac{w_i}{2v(\kappa)} \tag{A.6}$$

Eq. (A.6) shows that the spatial distribution of households plays a role in determining marginal commuting costs in a city with congestion through the variable velocity function and energy costs enter directly through the price of fuel and the fuel efficiency of travel embodied in the $G(v(\kappa))$ function.

A.6. Numerical solution of the UEFM

The model solution is computed by solving a two-equation system of differential equations with initial values. Given assumptions regarding the demand for housing services and the technology of housing production as well as fixed household income in the CBD, the SUM allows solution for the population density function, $D(T(k))$ in terms of commuting cost.[31] Total population housed within distance κ of the CBD is $N(\kappa) = 2\pi\theta\int_0^\kappa kD(T(k))dk$ where θ is the fraction of land used for housing. The number of households housed at distance κ is given by:

$$\frac{dn(\kappa)}{d\kappa} = 2\pi\theta\kappa D(T(\kappa)) \tag{A.7}$$

Recognizing that the $v(k)$ function depends on $N(k)$, Eqs. (A.6) and (A.7) imply a simultaneous relation between commuting costs and population distribution that must be solved as a system of first order differential equations.[32]

[31] The solution follows from Muth's equation where the fall in house price with distance is based on transportation cost or $dp/dk = -dT/dk/h$.

[32] Previous initial value problems used to simulate cities have involved the numerical solution of Eq. (A.7).

Fortunately the initial values for population and transportation costs at $k = 0$, the edge of the CBD, are known. Because no population is housed inside the CBD and employment inside the CBD is a known constant, the number of commuters to the CBD at its edge is known to be E_{CBD}. Highway capacity at the edge of the CBD is also known and equal to $H(0)$. Velocity and travel time can be computed as $v(0)$ and $t(0)$ based on $H(0)$ and E_{CBD}. The system of differential equations with initial values to be solved can be written as:

$$\begin{aligned}\frac{dT(k)}{dk} &= m_1 + \frac{p_g}{g(v(V(E_L(k),N(k),H(k))))} + \frac{w}{2v(V(E_L(k),N(k),H(k)))}\\ \frac{dN(k)}{dk} &= 2\pi\theta kD(T(k))\end{aligned} \tag{A.8}$$

with initial values

$$\begin{aligned}T(0) &= m_0 + k_{CBD}\left[m_1 + \frac{p_g}{g\left(v\left(V\left(E_L^T,0,H(0)\right)\right)\right)} + \frac{w}{2v\left(V\left(E_L^T,0,H(0)\right)\right)}\right]\\ N(0) &= 0\end{aligned} \tag{A.9}$$

where E_L^T is total local employment in the city and $N(0) = 0$ because no households live within the CBD. Recall that the distribution of local employment is predetermined along with the spatial distribution of highway capacity. Thus there are two covariates, $N(k)$ and $T(k)$, in the system of ordinary differential equations (A.8) and (A.9) with known initial values at the edge of the CBD where $k = 0$.

There is no explicit solution to this system of differential equations due to the complexity of the functional forms. Instead, the system is solved numerically. Once the commuting cost and number of households living in each annulus of the city are computed, it is possible to solve for all other variables that characterize the city because, as is generally the case with the SUM, the housing price, housing consumption per household, and housing production at each distance are determined by commuting cost from that location due to the iso-utility and zero-profit equilibrium conditions.

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