Modeling constraints versus modeling utility maximization: Improving policy sensitivity for integrated land-use/transportation models

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Abstract

Traditionally, integrated land-use/transportation models intend to represent all opportunities of travel and household location, maximize utilities and find an equilibrium in which no person or household could improve their satisfaction any further. Energy scarcity, higher transportation costs and an increasing share of low-income households, on the other hand, demand special attention to represent constraints that households face, rather than opportunities for utility maximization. This paper describes the integrated land-use model SILO that explicitly represents various constraints, including the price of a dwelling, the travel time to work and the monetary transportation budget. SILO ensures that no household makes choices that violate these constraints. Implementing such constraints helps SILO to generate more realistic results under intense scenarios, such as a serious increase in transportation costs or severely increased congestion.

1 Introduction

Households looking for a new place to live attempt to fulfill as many of their location preferences as possible. In reality, however, households face a couple of constraints in the housing search. First and foremost, the price of a new dwelling is a constraint. Even though loans and bank credits allow households to afford places that exceed their currently available budget, households have to get along with their income in the long run. Therefore, low-income households cannot afford moving into the nicest houses on the market. The income is an obvious constraint on housing choice.

Another constraint households face when looking for a new dwelling is travel time. An analysis of the 2007-2008 TPB/BMC Household Travel Survey for the Washington/ Baltimore region revealed that 86% travel less than 60 min to work, and 99% travel less than 120 min to work. Thus, commuting for no more than two hours is another constraint. Work locations are even more restrictive if more than one household member is working. Given that the average time spent on commuting does not change much over time [1], this constraint is not expected to alter much in the future. As a consequence, workers should be expected to move closer to their work location if congestion worsens, unless they have the opportunity to telework.

A third constraint is concerned with the total household budget. According to the Consumer Expenditure Survey[1], the average U.S. household spends 15.1% of its income on transportation. Should transportation become more expensive, households have to either adjust their travel behavior or reallocate their income. In reality, both happen. In some cases, particularly for low-income households, an increase in gas prices may trigger a household relocation to a less expensive apartment to ensure that the households gets along with its income in the long run.

The literature review (section 2) shows that the majority of land-use models do not represent such constraints explicitly. Section 3 introduces the land-use model SILO, and section 4 explains how constraints are treated in SILO. Section 5 ends this paper with conclusions and recommendations for future research.

2 Literature review

One of the pioneering land-use models was designed by John D. Herbert and Benjamin H. Stevens [2] in cooperation with Britton Harris as an equilibrium model simulating distribution of households to residential land use. Lowry's Model of Metropolis [3, 4] is often considered to be the first computer model that truly integrated land use and transportation. The Lowry Model assumed the location of basic employment exogenously and generated an equilibrium for the allocation of non-basic employment and population. Over the last five decades, this popular model has been implemented many times [e.g., 5, 6, 7]. At least equally influential was Forrester's Theory of Urban Interactions [8]. Even though it was an aspatial model, his description of interactions between population, employment and housing has led the design of many spatial land use models developed ever since.

Putman developed the Integrated Transportation and Land Use model Package (ITLUP) [9, 10], where land use was modeled by the Projective Land-Use Model (PLUM) [11-13]. Later, PLUM was replaced by the frequently applied Disaggregated Residential Allocation Model (DRAM) and an Employment Allocation Model (EMPAL).

Wilson's Entropy Model [14, 15] generated an equilibrium by maximizing entropy of trips, goods flows or the distribution of population. Anas' [16] model called Residential Location Markets and Urban Transportation created an equilibrium between demand, supply and costs for housing. Anas' model is not deterministic by assigning each dwelling to the highest-paying buyer, but rather probabilistic to represent variance in preferences and decisions.

The MEPLAN model developed by Echenique is an aggregated land-use transport model [17-19] that used the basic concept of the Lowry model as a starting point. The model can simulate a variety of both land-use and transport scenarios. MEPLAN has been applied to more than 25 regions worldwide [20: 332]. Another modeling approach using the Lowry

[1] Available online at http://www.bls.gov/cex/#tables

model as a starting point is the TRANUS model [21: 143 ff, 22, 23] that simulates land use, transport, and its interactions at the urban and regional scale.

Martínez [24, 25] developed a land-use model under the acronym MUSSA in which location choice is modeled as a static equilibrium. Residential and commercial land-use developments compete for available land. MUSSA used the bid-auction approach based on the bid-rent theory where consumers try to achieve prices as low as possible and not higher than their willingness to pay [26]. In the bid-rent theory, first introduced by Alonso [27: 36 ff], land prices are an immediate result of the bid-auction process. In contrast, the discrete-choice approach -initially developed for housing choice by McFadden [28: 76 ff]- models land being bought or rented with no instant effect on the price. Acknowledging that both approaches lead to equivalent results, Martínez argues elsewhere [26: 884 f] that the bid-auction approach and the discrete-choice approach should be integrated and seen as inseparable rather than opposed.

PECAS [29, 30] is another land use model that represents an equilibrium of competing demand for developable land. Households relocate based on available floorspace, prices, accessibilities and other location factors. PECAS combines this bid-rent approach in a spatial economic model with a microscopic land development model. DELTA [31] combines an economic model with households and job location model and a long-distance migration model.

Wegener [32-34] developed the IRPUD model as a fully integrated land-use transport model. The household location choice is microscopic [35], simulating every household individually. The IRPUD model was one of the few early approaches that contradicted the common assumption that land-use models shall reach an equilibrium at the end of each simulation period [36]. Land-use development aims at equilibrium constantly, but due to a continuously changing environment and slow reaction times of households, businesses, developers, and planners this equilibrium stage is never reached. The price of a new dwelling and the commute distance to the household's main workplace are accounted for as true constraints in location choice. Similarly, the Metroscope model for Portland, Oregon [37] compares expenditures for housing, transportation, food, health and all other expenses to ensure that household budgets are not exceeded.

Microsimulation was introduced by Orcutt [38: 45 ff.] and subsequently applied to a series of modeling tasks, including travel behavior, demographic change, spatial diffusion, health and land use [39: 156 ff.]. The most influential microscopic land use models include the California Urban Futures (CUF) Model [40, 41], the Integrated Land Use, Transport and Environment (ILUTE) model [42-44], the Urban Simulation (UrbanSim) model at the University of Washington, Seattle [45, 46], the Learning-Based Transportation Oriented Simulations System (ALBATROSS) [47], Predicting Urbanisation with Multi-Agents (PUMA) [48], SimDELTA [31] and the Integrated Land-Use Model And transportation System Simulation (ILUMASS) [49, 50].

Good overviews of operational land-use/transport models are given particularly by Hunt et al. [20], Wegener [51-53], Wegener and Fürst [54: 42 ff], Timmermans [55], Kanaroglou and Scott [56], the U.S. Environmental Protection Agency EPA [57: 27 ff], or Kain [58]. The literature review showed that the majority of land use models do not explicitly represent constraints. The majority of models lead to an equilibrium reaching an "ideal" distribution of households and land uses. Commonly, land use is viewed as a decision-making process in which users optimize their utilities, rather than making choices among a limited set of alternatives. Notable exceptions are the IRPUD model Metroscope, which explicitly constrain households to move to dwellings that are within their respective price range.

3 The land use model SILO

SILO was designed as a microscopic discrete choice model. Every household, person and dwelling is treated as an individual object. All decisions that are spatial (household relocation and development of new dwellings) are modeled with Logit models. Initially developed by Domencich & McFadden [59], such models are particularly powerful at representing the psychology behind decision making. Other decisions (such as getting married, giving birth to a child, leaving the parental household, upgrading an existing dwelling, etc.) are modeled with Markov models by applying transition probabilities.

SILO is built as a middle-weight tool. To fully represent interactions between land use and transportation, SILO is fully integrated with the Maryland Statewide Transportation Model (MSTM). On the other hand, it is built to work with less rigorous data collection and estimation requirements than traditional large-scale land-use models (such as PECAS or UrbanSim), making SILO simpler to implement. Figure 1 provides an overview of the SILO model.

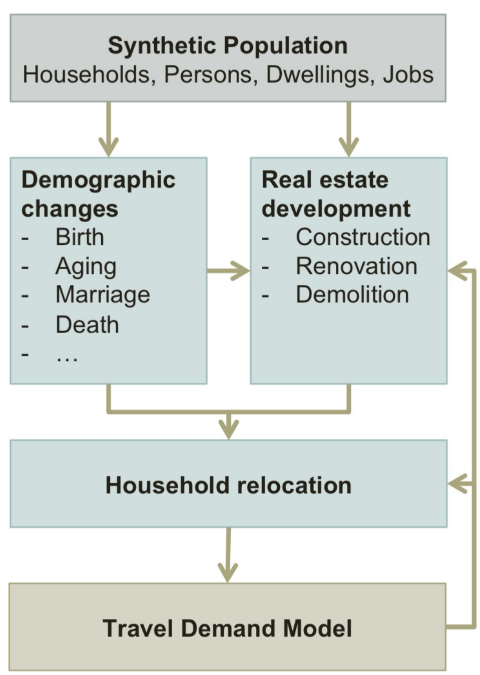

Figure 1: Model flowchart for SILO

At the beginning, a synthetic population is created for the base year 2000. The Public Use Micro Sample (PUMS) 5% dataset[2] is used to create this synthetic population. Using expansion factors provided by PUMS, household records with their dwelling are duplicated until the population by PUMS zone (called PUMA) matches 2000 census data. The location is disaggregated from PUMA to model zones using the socio-economic data of the MSTM as a weight. Work places are created based on MSTM zonal employment data. For each worker, a work location is chosen based on the average commute trip length distribution found in the 2007-2008 TPB/BMC Household Travel Survey. SILO simulates events that may occur to persons, households and dwellings:

- Household
    - Relocation
    - Buy or sell cars
- Person
    - Aging
    - Leave parental household
    - Marriage
    - Birth to a child
    - Divorce
    - Death
    - Find a new job
    - Get laid off
- Dwelling
    - Construction of new dwellings
    - Renovation
    - Deterioration
    - Demolition
    - Increase or decrease of price

These events are modeled in random order. The random order avoids path dependency and models events as they happen in reality: Someone celebrates a birthday, somewhere a household moves, another house is renovated, etc. SILO is calibrated to match observed land use changes from 2000 to 2010 (so-called backcasting), to reasonable model changes of population and housing into the future to the year 2040.

SILO is open-source software and was initially developed with research funding by Parsons Brinckerhoff, Inc. The prototype application was implemented for the Metropolitan Area of Minneapolis/St. Paul, Minnesota. Currently, the Maryland Department of Transportation supports the implementation of an improved version for the State of Maryland. SILO provides a GUI (Graphical User Interface) to facilitate model applications. A visualization tool is included for the analysis of model results. Further information on model design and implementation can be found at www.silo.zone.

[2] Available for download at http://www2.census.gov/census_2000/datasets/PUMS/FivePercent/

4 Modeling constraints

SILO explicitly represents several constraints households face in location choice. Following, three constraints are described in more detail, namely housing costs, commute travel time and household transportation budget.

4.1 Housing cost constraint

The costs of a dwelling form an immediate constraint on any relocation choice. While households may exceed their housing budget temporarily, households have to get along with their income in the long run. The distribution of rent and mortgage payments in the base year according to PUMS data is used as guidance on how much households are willing to pay for housing. Figure 2 shows the aggregation to reveal the willingness to pay rent or to pay for a mortgage. As expected, higher income households tend to pay higher rents than low-income households.

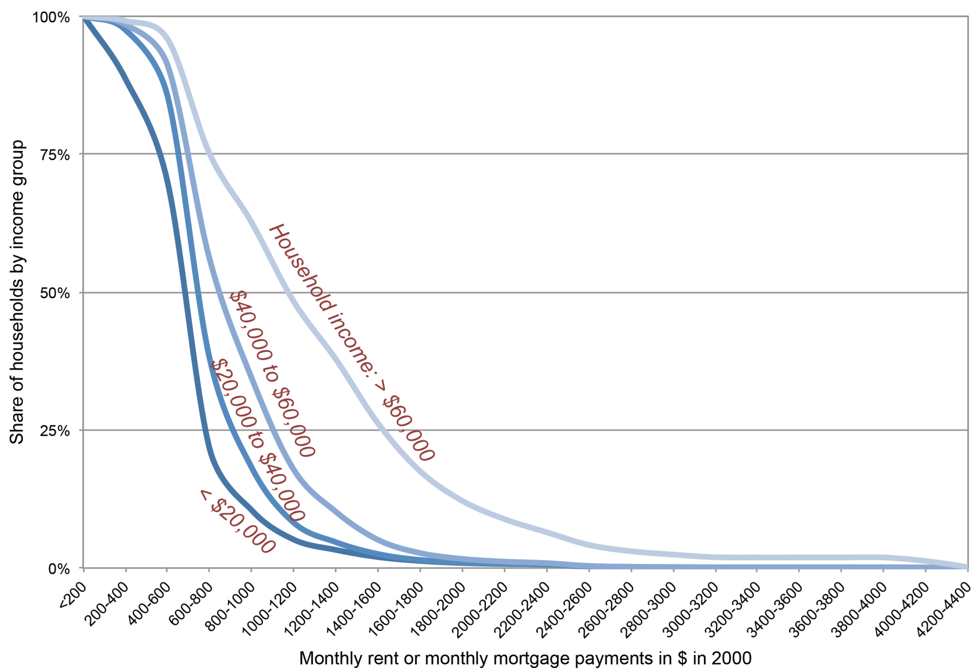

Figure 2: Willingness to pay rent by household income (Source: PUMS 2000 database)

The relationship between income and housing expenses shown in Figure 2 is used to calculate the utility of a given price using equation 1.

$$util_{p_d} = 1 - \sum_{price_j}^{price_j < price_i} hhShare_{price_j,inc} \qquad \text{Equation 1}$$

where:

$util_{p_d}$	Utility of price p of dwelling d
$hhShare_{price_j,inc}$	Share of households with income *inc* who have paid $price_j$ in base year

The higher the price, the lower the utility, and the utilities decline faster for low-income households than for high-income households. When the share of households paying a certain amount of rent reaches zero, the utility becomes zero and that dwelling becomes unavailable for this household type.

4.2 Commute travel time constraint

The travel time to work is a principal driver for household location choice. With the exception of workers who regularly work from home, the travel time from home to work is an important constraint when choosing a new place to live. Travel time to work is remarkably constant over time [1, 60]. The aforementioned TPB/BMC household travel survey was analyzed for the time spent on home-to-work trips. Figure 3 shows estimated gamma functions representing the observed trip length frequency distribution for commute trips. Because respondents tend to round their travel time to even numbers (for example, 12 percent reported their commute to be exactly 30 min), the observed trip length frequency distribution is lumpy and needs to be interpolated. The gamma function shown in Figure 3 was calibrated to match the reported average trip length.

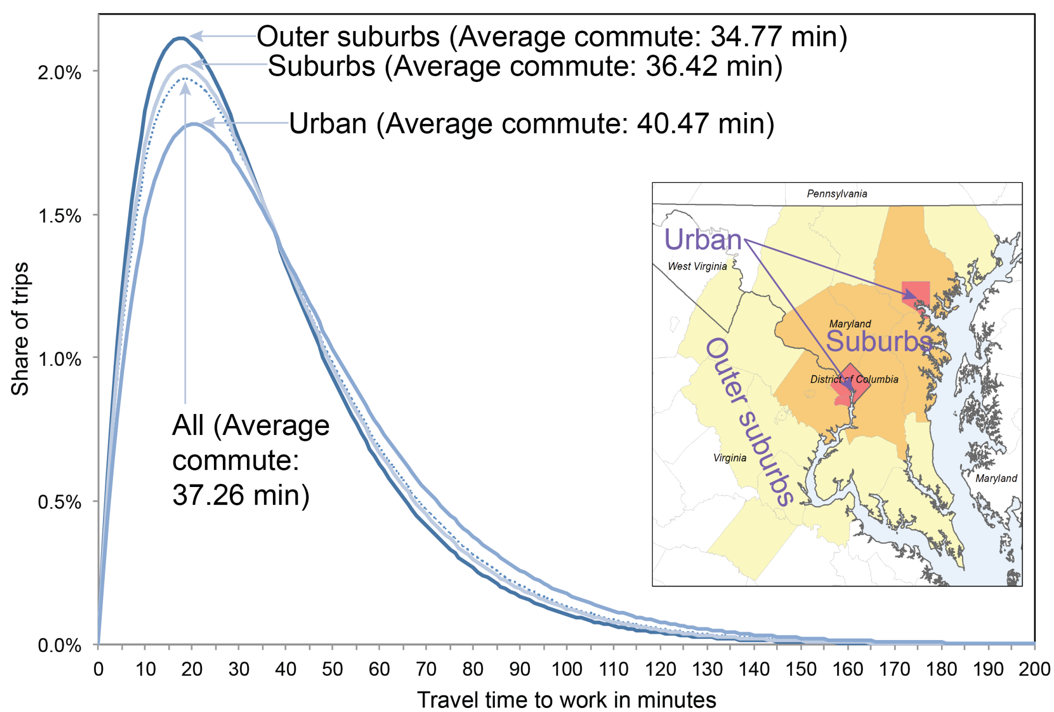

Figure 3: Estimated commute travel time for rural, suburban and urban residents

Residents living in the urban counties in Baltimore, Washington, Arlington and Alexandria have above-average commute times. Even though their average trip lengths with 9.8 miles is shorter than the average commute trip length of outer suburbs residents (15.5 miles), urban residents have to cope with more severe congestion, and therefore, need more time to get to work. Also, the transit share is much higher in urban areas, which often leads to longer travel times. The trip length frequency distributions in time are expected to not change significantly in the future. When households look for a new housing location, the job location of all workers of this household are taken into account. Housing locations that are too far from the household's work locations receive a low utility closer to zero.

The left map in Figure 4 shows an example of a work location in North Bethesda, MD (turquoise dot). The trip length frequency distribution of the household travel survey is used to estimate the utility in terms of commute distance for every other zone (shown in brown-to-yellow colors).

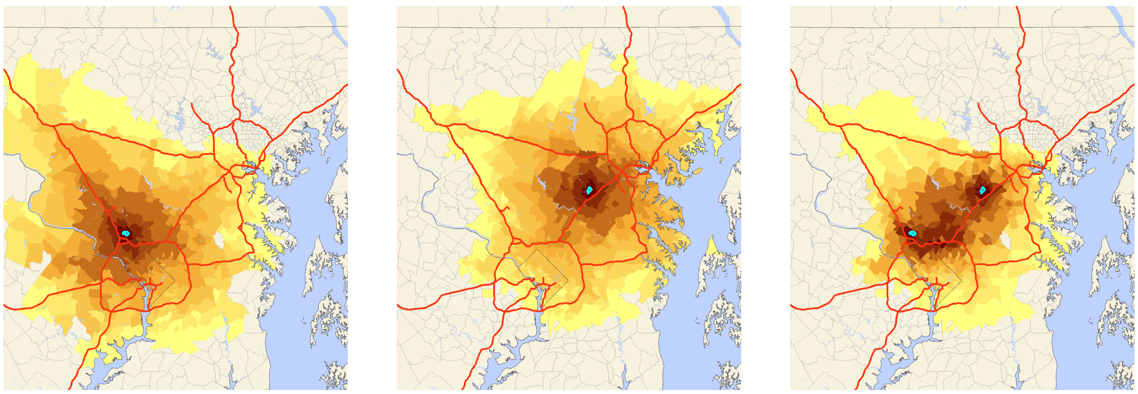

Figure 4: Likely housing locations for a household with workers in North Bethesda (left), Columbia (center) and both (right)

The map in the center shows the home location probability for a person working in Columbia, MD. If these two persons lived in the same household, their joint area within a reasonable distance to their work locations would be shown in the map on the right side of Figure 4. SILO explicitly represents this constraint when searching for a new housing location. The average commute trip length frequency shown in Figure 3 with a dotted line is scaled to values between 0 and 1 and applied as the commute distance utility.

Unfortunately, telework is not represented explicitly in SILO at this point. An employee working from home a few days per week is likely to be less constrained by the location of her or his employer and willing to accept longer commute travel times for the few days this person is actually commuting to the work location. It is planned to enhance the model to allow certain occupations types to telecommute, and thereby, offset some of their travel time budget.

4.3 Household budget constraint

Another constraint explicitly reflected in SILO covers household expenditures. According to the Consumer Expenditure Survey[3] of the Bureau of Labor Statistics, households spent an average of 13 percent of their income on transportation. Low-income

[3] Data available online at http://www.bls.gov/cex/home.htm

households spent as much as 28% of their income on transportation. If transportation costs rise, households will be required to shift expenses. While affluent households will simply reduce savings or discretionary spending to cover increased transportation costs, low-income households may struggle to cover substantially higher transportation costs. A household searching for a new home will estimate transportation costs and consider carefully if transportation costs at a given home location are within the budget. A low-income household may decide to locate closer to the work location or choose a transit-friendly environment that may allow reducing the number of cars owned by the household.

Figure 5 compares average income with average expenditures for households with different incomes. The plot shows data for SILO's base year 2000, data for 2005 and 2010 were analyzed and displayed very similar patterns. Interestingly, households in income categories with an annual pre-tax income below $41,499 on the average spend more money then they earned. According to the BLS, such households draw on savings or borrow money. Students may get by on loans and retirees may rely on savings[4]. As SILO does not trace debts a household may temporarily accumulate, it is simply acknowledged that households have access to money to cover their expenses. For example, a household with an after-tax income of $7,192 (left-most point in Figure 5) is assumed to have access to $15,703 to spend.

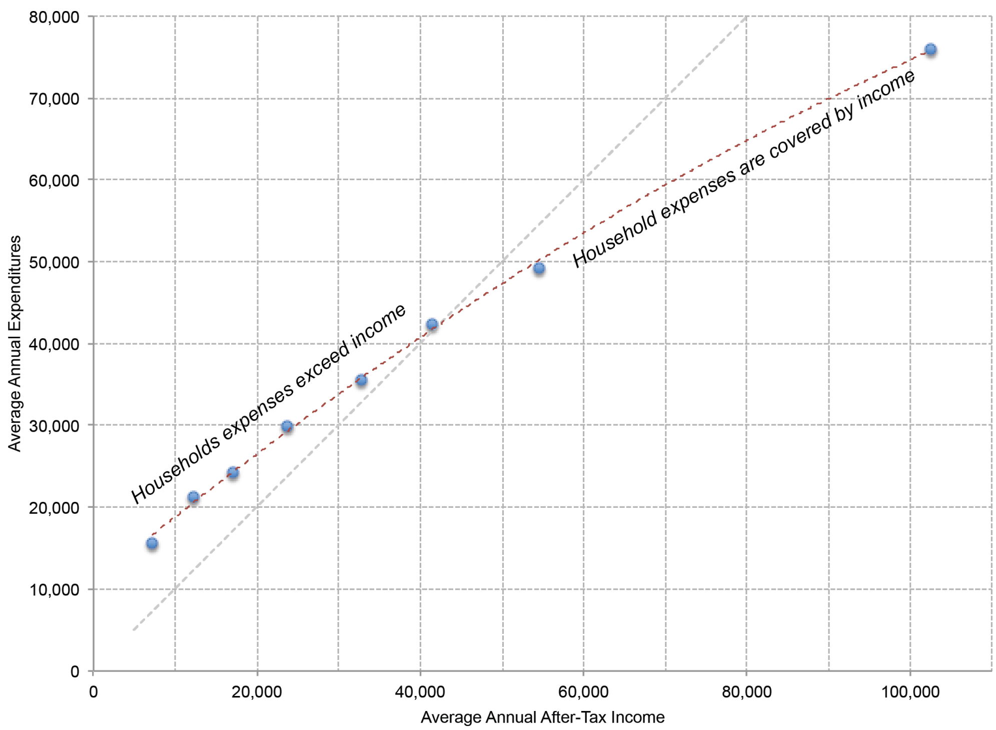

Figure 5: Household income and expenditures (Source: Consumer Expenditure Survey, BLS)

A polynominal curve has been estimated to reflect the relationship between income and expenditures (shown with a red dashed line in Figure 5). For household incomes greater

[4] For a more detailed discussion of this phenomenon compare http://www.bls.gov/cex/csxfaqs.htm#q21

than $41,499 (whose income exceeds expenditures), the entire income is assumed to be available for expenditures, even though the average household at that income level tends to save some money. Due to the parameter γ, the available money for expenditures can never drop below $10,794, even if the household income is 0.

$$e_h = \max\left[inc, \left(\alpha \cdot inc_h^2 + \beta \cdot inc_h + \gamma\right)\right] \qquad \textit{Equation 2}$$

where:

e_h	Budget available for expenditures of household h
inc_h	Income of household h
α, β, γ	Parameters, estimated to α = -2E-6, β = 0.8229 and γ = 10,794

According to the Consumer Expenditure Survey, expenses for gasoline and motor oil make up between 3.8 percent of all household expenses for high-income and 5.3 percent for households with an average income. Though this may not seem high, an increase of travel costs may become a serious burden for low-income households. Litman [61] suggested that fuel price elasticity is between -0.1 and -0.2 for short run and between -0.2 and -0.3 for medium run adjustments. Short-run adjustments include choosing different trip destinations and switching the mode, while long-run adjustments (which typically apply after one to two years) include the purchase of more fuel-efficient vehicles and selecting more accessible home and job locations. Because a household move is part of a medium- to long-run adjustment, the higher elasticity with an average of -0.25 was chosen in SILO: Should gas prices increase by 10 percent, travel demand is expected to decline by 2.5 percent. Transportation *tc* costs are calculated based on auto-operating costs (set to 8.1 cents per mile in the base scenario), the distance to work and transportation required for other purpose, such as shopping, dropping off children at childcare, doctor visits, etc. For a scenario that analyzes the impact of higher fuel costs, the adjusted transportation expenditures are calculated by

$$et_h = tc_s\left(1 + \tfrac{tc_s - tc_b}{tc_b} \cdot el\right) \qquad \textit{Equation 3}$$

where:

et_h	Expenditures of household h for transportation
tc	Transportation costs (b for base case and s for alternative scenario)
el	Elasticity of travel demand on transportation costs, set to -0.25

In addition to adjusting travel behavior and locations, many households will need to rebalance expenditures if transportation costs rise. Figure 6 shows the relative size of various expenditure types. The total expenditure is identical to the expenditure line shown in Figure 5, and the shares of various expenditure categories were estimated equally by a polynominal function using observations of the Consumer Expenditures Survey. A certain share of “Other expenditures” is assumed to be discretionary and could be used to offset increased transportation costs. No data were available to quantify discretionary spending, and a few data points[5] were assumed to estimate a smooth curve for the discretionary spending shown in Figure 6.

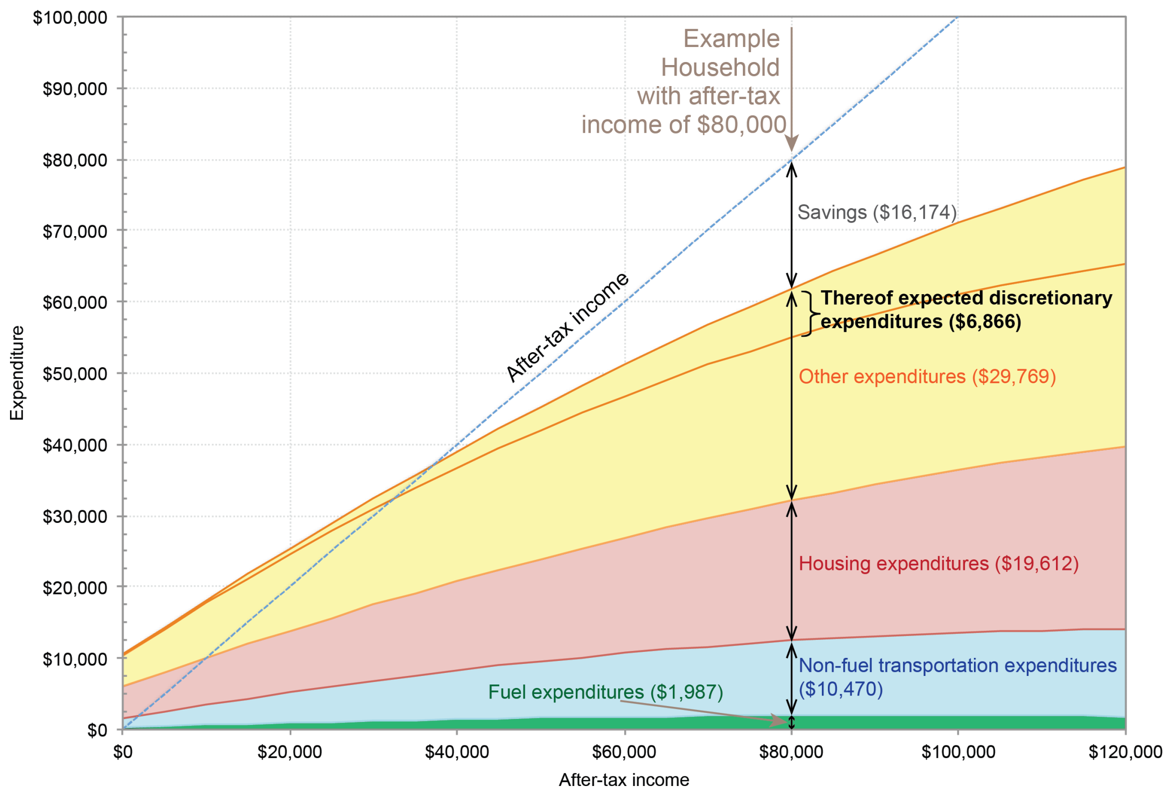

Figure 6: Share of expenditure types by household income (Source: Consumer Expenditure Survey, BLS)

A binomial logit model (equation 4) is used to calculate the utility for transportation costs. If the discretionary income and savings are insufficient to cover the transportation costs of a given dwelling, the utility for transportation costs at this dwelling is set to 0.

if $(e_{dis,h} + s_h < tc)$: $\quad util_{tb_d} = 0$

if $(e_{dis,h} + s_h >= tc)$: $\quad util_{tb_d} = \dfrac{1}{1+\exp\left(\beta \cdot \frac{e_{dis,h}+s_h}{tc}\right)}$ *Equation 4*

where:

$util_{tb_d}$	Utility of dwelling *d* for transportations budget *tb*
β	Parameters describing sensitivity of increased transportation costs
$e_{dis,h}$	Discretionary expenditures of household *h*
s_h	Savings of household *h*

[5] Assumed data points for Income/discretionary spending: [$0/$100; $20,000/$1,000; $40,000/$2,200; $100,000/$10,000; $150,000/$20,000]

For households with a higher income, this utility will always be close to 1, as an increase in transportation costs is insignificant for these households. Households with lower incomes, however, will find a lower utility if transportation costs at a given dwelling are high. Should transportation costs exceed the discretionary income plus savings, the utility for the dwelling will be set to 0, which prevents this household from moving into this dwelling.

4.4 Merging utilities

In addition to housing costs, commute travel times and transportation costs (described sections 4.1 to 4.3), a number of further location attributes are included that are deemed to be desirable but non-essential. Such location factors include the size and the quality of the new dwelling and the accessibility to population and employment by auto and transit. While these location factors are desirable, one strong attribute may compensate for another weak attribute. For example, a house in the suburbs may be weak in terms of accessibility but strong in terms of size. In contrast, urban apartments tend to be weak in size but provide excellent accessibilities. A strong attribute may offset a weak attribute, depending on the household preferences. Those location factors are summarized by weighted addition:

$$urf_d = \alpha \cdot u_{size_d} + \beta \cdot u_{quality_d} + \gamma \cdot u_{autoAcc_d} + (1 - \alpha - \beta - \gamma) \cdot u_{transitAcc_d} \qquad \text{Equation 5}$$

where:

urf_d	Utility of replaceable factors for dwelling *d*
α, β, γ	Parameters as weights for each factor, distinguished by household types
u_{factor_d}	Utility of attribute of dwelling *d* (e.g., size, quality, auto accessibility or transit accessibility)

In contrast to replaceable utilities, essential utilities are assumed to be mandatory to be fulfilled. For example, if a dwelling is too expensive for a household, the total utility for this dwelling shall be set to 0 for this particular household. This is achieved by using the Cobb-Douglas function that aggregates utilities by multiplication:

$$u_d = urf_d^{\alpha} \cdot util_{p_d}^{\beta} \cdot util_{ct_d}^{\gamma} \cdot util_{tb_d}^{(1-\alpha-\beta-\gamma)} \qquad \text{Equation 6}$$

where:

u_d	Utility of dwelling *d*
urf_d	Utility of replaceable factors of dwelling *d*
$util_{p_d}$	Utility of the price of dwelling *d*
$util_{ct_d}$	Utility of the commute time for dwelling *d*
$util_{tb_d}$	Utility of the transportation budget required for dwelling *d*
α, β, γ	Parameters as weights for each factor, distinguished by household types

Using a multiplication to aggregate essential location factors ensures that if one utility is 0, the entire utility for this dwelling will becomes 0. This way, it is ensured that households do not move into a place that violates budget constraints.

5 Conclusions

Many land-use models focus on utility maximization, finding equilibriums and optimally allocating limited resources. The famous Lowry model is built to reach an equilibrium between location of work places and location of households every simulation period [3]. Similarly, most models using Alonso's bid-rent approach [27] assume an immediate equilibrium between land prices and demand for land. Dynamic urban models, in contrast, explicitly represent time delay and limited information that lead to imperfect equilibriums [62, 63]. While bid-rent models are assumed to better represent land-use prices, discrete choice models often are expected to more realistically represent delays as they happen in reality. For example, new demanded housing is not available to move in right away, but planning, obtaining building permissions and construction may take several years from when the demand is realized to when the first household may move in. While SILO follows the discrete choice modeling paradigm, the true benefits of either approach could best be determined by meta analyses that test the same scenarios in different models [64].

Wegener [65: 753-755] identified three principal challenges for land-use modeling: Modeling environmental impacts, being able to model decline rather than growth, and modeling the impacts of the future energy crises. Testing policies that address environmental impacts, such as carbon taxes, road pricing or energy-efficient buildings has an immediate impact on household budgets. Planning for decline requires reallocating limited resources, including closing of schools or redevelopment of brownfield sites. A future energy crisis may limit the availability of fossil fuels for transportation or heating and cooling, with an immediate impact on household mobility and budgets. If these challenges hold true, representing constraints will become even more important. If models miss representing changes in travel behavior and location choice under increasing transportation costs, model results will be less realistic and difficult to defend. If congestion worsens and people spend more time traveling, models that miss adjusting destination choice, mode choice and trip chaining will produce unlikely results. Representing constraints rather than the entire map of opportunities will become more important in a scarce energy future.

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References

1. Zahavi, Y., M.J. Beckmann, and T.F. Golob, *The UMOT/Urban Interactions*. 1981, Washington D.C.: U.S. Department of Transportation. 151.
2. Herbert, J.D. and B.H. Stevens, *A model for the distribution of residential activity in urban areas.* Journal of Regional Science, 1960. **2**(2): p. 21-36.
3. Lowry, I.S., *A Model of Metropolis. Memorandum RM-4035-RC*. 1964, Santa Monica: Rand Corporation.
4. Lowry, I.S., *Migration and Metropolitan Growth: Two Analytical Models*. 1966, San Francisco: Chandler. 118.
5. Batty, M., *Urban Modelling. Algorithms, Calibrations, Predictions*. Cambridge Urban and Architectural Studies, ed. L. Martin. Vol. 3. 1976, London: Cambridge University Press. 381.
6. Wang, F., *Urban population distribution with various road networks: a simulation approach.* Environment and Planning B: Planning and Design, 1998. **25**: p. 265-278.
7. Mishra, S., et al., *A functional integrated land use-transportation model for analyzing transportation impacts in the Maryland-Washington, DC Region.* Sustainability: Science, Practice, & Policy, 2011. **7**(2): p. 60-69.
8. Forrester, J.W., *Urban Dynamics*. 1969, Cambridge (Massachusetts): The M.I.T. Press. 285.
9. Putman, S.H., *Integrated Urban Models. Policy Analysis of Transportation And Land Use*. Research in Planning and Design, ed. A.J. Scott. Vol. 10. 1983, London: Pion. 332.
10. Putman, S.H., *Integrated Urban Models 2. New Research And Applications of Optimization And Dynamics*. 1991, London: Pion. 355.
11. Rosenthal, S.R., J.R. Meredith, and W. Goldner, *Plan making with a computer model: Projective land use model*. Vol. 1. 1972, Berkeley: Institute of Transportation and Traffic Engineering. 92.
12. Goldner, W., S.R. Rosenthal, and J.R. Meredith, *Theory and Application: Projective Land Use Model*. Vol. 2. 1972, Berkeley: Institute of Transportation and Traffic Engineering. 180.
13. Reynolds, M.M. and J.R. Meredith, *Computer Systems Guide: Projective Land Use Model*. Vol. 3. 1972, Berkeley: Institute of Transportation and Traffic Engineering. 82.
14. Wilson, A.G., *Statistical Theory of Spatial Distribution Models.* Transportation Research, 1967. **1**: p. 253-269.
15. Wilson, A.G., *Entropy in Urban and Regional Modelling*. 1970, London: Pion. ca. 165.
16. Anas, A., *Residential Location Markets and Urban Transportation. Economic Theory, Econometrics, and Policy Analysis with Discrete Choice Models*. Studies in Urban Economics, ed. E.S. Mills. 1982, New York: Academic Press. 263.
17. Echenique, M.H., D. Crowther, and W. Lindsay, *A Spatial Model of Urban Stock and Activity.* Regional Studies, 1969. **3**: p. 281-312.
18. Echenique, M.H., et al., *The MEPLAN models of Bilbao, Leeds and Dortmund.* Transport Reviews, 1990. **10**(4): p. 309-322.
19. Abraham, J.E. and J.D. Hunt, *Firm Location in the MEPLAN Model of Sacramento.* Transportation Research Record, 1999. **1685**(Paper No. 99-1300): p. 187-198.

20. Hunt, J.D., D.S. Kriger, and E.J. Miller, *Current Operational Urban Land-use-Transport Modelling Frameworks: A Review.* Transport Reviews, 2005. **25**(3): p. 329-376.
21. de la Barra, T., *Integrated Land Use And Transport Modelling. Decision Chains and Hierarchies*. Cambridge Urban And Architectural Studies, ed. L. Martin. Vol. 12. 1989, Cambridge: Cambridge University Press. 179.
22. de la Barra, T. and P.A. Rickaby, *Modelling regional energy-use: a land-use, transport, and energy-evaluation model.* Environment and Planning B: Planning and Design, 1982. **9**(4): p. 429-443.
23. de la Barra, T., B. Pérez, and N. Vera, *TRANUS-J: putting large models into small computers.* Environment and Planning B: Planning and Design, 1984. **11**(1): p. 87-101.
24. Martínez, F.J., *Towards a Land-use and Transport Interaction Framework*, in *Handbook of Transport Modelling*, D.A. Hensher and K.J. Button, Editors. 2002, Pergamon: Amsterdam. p. 145-164.
25. Martínez, F.J., *MUSSA: Land Use Model for Santiago City.* Transportation Research Record, 1996. **1552**: p. 126-134.
26. Martínez, F.J., *The bid-choice land-use model: an integrated economic framework.* Environment and Planning A, 1992. **24**(6): p. 871-885.
27. Alonso, W., *Location and Land Use. Towards a General Theory of Land Rent*. 1964, Cambridge, Massachusetts: Harvard University Press. 204.
28. McFadden, D., *Modelling the choice of residential location*, in *Spatial Interaction Theory and Planning Models*, A. Karlqvist, et al., Editors. 1978, North-Holland Publishing Company: Amsterdam, New York, Oxford. p. 75-96.
29. Hunt, J.D. and J.E. Abraham, *PECAS - for Spatial Economic Modelling. PECAS - for Spatial Economic Modelling*. 2009, HBA Specto Incorporated: Calgary, Alberta.
30. Hunt, J.D. and J.E. Abraham, *Design and application of the PECAS land use modelling system*, in *8th International Conference on Computers in Urban Planning and Urban Management*. 2003: Sendai, Japan.
31. Simmonds, D.C. and O. Feldman, *Advances in integrated urban/regional land-use/transport modelling using the DELTA package*, in *World Conference on Transport Research (WCTR)*. 2007: Berkeley, CA.
32. Wegener, M., *Die Stadt der kurzen Wege: Müssen wir unsere Städte umbauen?* 1999, Institut für Raumplanung: Dortmund. p. 52.
33. Wegener, M. *The IRPUD Model: Overview*. 1998 20 Sept 2005]; Available from: http://www.raumplanung.uni-dortmund.de/irpud/pro/mod/mod_e.htm.
34. Wegener, M., *Modeling Urban Decline: A Multilevel Economic-Demographic Model for the Dortmund Region.* International Regional Science Review, 1982. **7**(2): p. 217-241.
35. Wegener, M., *Räumliches Wahlverhalten unter ökonomischen und informationellen Restriktionen: Ein mikroanalytisches Modell des Wohnungsmarkts*, in *Theorie und Quantitative Methodik in der Geographie*, G. Bahrenberg and M.M. Fischer, Editors. 1984, Universität Bremen: Bremen. p. 92-136.
36. Wegener, M., F. Gnad, and M. Vannahme, *The Time Scale of Urban Change*, in *Advances in Urban Systems Modelling*, B. Hutchinson and M. Batty, Editors. 1986, Elsevier Science Publishers B.V. (North-Holland): Amsterdam. p. 175-197.
37. Conder, S. and K. Lawton, *Alternative Futures for Integrated Transportation and Land-Use Models Contrasted with Trend-Delphi Models.* Transportation Research Record: Journal of the Transportation Research Board, 2002. **1805**: p. 99-107.

38. Orcutt, G.H., et al., *Microanalysis of Socioeconomic Systems: A Simulation Study*. 1961, New York: Harper & Brothers. 425.
39. Clarke, M. and E. Holm, *Microsimulation methods in spatial analysis and planning.* Geografiska Annaler. Series B. Human Geography, 1987. **69 B**: p. 145-164.
40. Landis, J. and M. Zhang, *The second generation of the California urban futures model. Part 1: Model logic and theory.* Environment and Planning B: Planning and Design, 1998. **25**: p. 657-666.
41. Landis, J. and M. Zhang, *The second generation of the California urban futures model. Part 2: Specification and calibration results of the land-use change submodel.* Environment and Planning B: Planning and Design, 1998. **25**: p. 795-824.
42. Miller, E.J., et al., *Microsimulating urban systems.* Computers, Environment and Urban Systems, 2004. **28**: p. 9-44.
43. Miller, E.J. and P.A. Salvini, *The Integrated Land Use, Transportation, Environment (ILUTE) Microsimulation Modelling System: Description and Current Status*, in *Travel Behaviour Research. The Leading Edge*, D.A. Hensher, Editor. 2001, Pergamon: Amsterdam. p. 711-724.
44. Salvini, P.A. and E.J. Miller. *ILUTE: An Operational Prototype of a Comprehensive Microsimulation Model of Urban Systems*. in *10th International Conference on Travel Behaviour Research*. 2003. Lucerne.
45. Waddell, P., *UrbanSim. Modeling Urban Development for Land Use, Transportation, and Environmental Planning.* Journal of the American Planning Association, 2002. **68**(3): p. 297-314.
46. Waddell, P., et al., *Microsimulation of Urban Development and Location Choice: Design and Implementation of UrbanSim.* Networks and Spatial Economics, 2003. **3**: p. 43-67.
47. Arentze, T. and H. Timmermans, *ALBATROSS - A Learning Based Transportation Oriented Simulation System*. 2000, Eindhoven: European Institute of Retailing and Services Studies.
48. Ettema, D., et al. *PUMA (Predicting Urbanisation with Multi-Agents): a multi-agent approach to modelling urban development and processes*. in *Integrated assessment of the land system: The future of land use*. 2004. Amsterdam.
49. Strauch, D., et al., *Linking Transport and Land Use Planning: The Microscopic Dynamic Simulation Model ILUMASS*, in *GeoDynamics*, P.M. Atkinson, et al., Editors. 2005, CRC Press: Boca Raton. p. 295-311.
50. Wagner, P. and M. Wegener, *Urban Land Use, Transport and Environment Models. Experiences with an Integrated Microscopic Approach.* disP, 2007. **170**(3): p. 45-56.
51. Wegener, M., *Overview of Land Use Transport Models*, in *Handbook of Transport Geography And Spatial Systems*, D.A. Hensher, et al., Editors. 2004, Elsevier: Amsterdam. p. 127-146.
52. Wegener, M., *Applied Models of Urban Land Use, Transport and Environment: State of the Art and Future Developments*, in *Network Infrastructure and the Urban Environment. Advances in Spatial Systems Modelling*, L. Lundqvist, L.-G. Mattsson, and T.J. Kim, Editors. 1998, Springer: Berlin. p. 245-267.
53. Wegener, M., *Operational Urban Models.* Journal of the American Planning Association, 1994. **60**(1): p. 17-29.
54. Wegener, M. and F. Fürst, *Land-Use Transport Interaction: State of the Art*. 1999, Institut für Raumplanung: Dortmund. p. 99.
55. Timmermans, H. *The Saga of Integrated Land Use-Transport Modeling: How Many More Dreams Before We Wake Up? Conference keynote paper*. in *Moving through*

nets: The physical and social dimensions of travel. 10th International Conference on Travel Behaviour Research. 2003. Lucerne.

56. Kanaroglou, P.S. and D.M. Scott, *Integrated Urban Transportation and Land-use Models for Policy Analysis*, in *Governing Cities on the Move. Functional and management perspectives on transformations of European urban infrastructures*, M. Dijst, W. Schenkel, and I. Thomas, Editors. 2002, Ashgate: Hamshire (England), Burlington (VT). p. 42-72.
57. U.S. Environmental Protection Agency, *Projecting Land-Use Change. A Summary of Models for Assessing the Effects of Community Growth and Change on Land-Use Patterns*. 2000, Cincinnati: U.S. Environmental Protection Agency, Office of Research and Development. 260.
58. Kain, J.F., *Computer simulation models of urban location*, in *Handbook of regional and urban economics. Volume II: Urban Economics*, E.S. Mills, Editor. 1987, North-Holland: Amsterdam. p. 847-875.
59. Domencich, T.A. and D. McFadden, *Urban Travel Demand. A behavioural analysis*. Contributions to Economic Analysis. Vol. 93. 1975, Amsterdam, Oxford: North-Holland Publishing. 215.
60. van Wissen, L.J., T.F. Golob, and H.J. Meurs, *A Simultaneous Dynamic Travel And Activities Time Allocation Model*, in *University of California Transportation Center: Faculty Research*. 1991: Berkeley, CA. p. 17.
61. Litman, T., *Changing North American vehicle-travel price sensitivities: Implications for transport and energy policy.* Transport Policy, 2013. **28**(0): p. 2-10.
62. Harris, B.J. and A.G. Wilson, *Equilibrium values and dynamics of attractiveness terms in production-constrained spatial-interaction models.* Environment and Planning A, 1978. **10**(4): p. 371-388.
63. Wegener, M., *Transport network equilibrium and regional deconcentration.* Environment and Planning A, 1986. **18**: p. 437-456.
64. Wegener, M., R.L. Mackett, and D.C. Simmonds, *One city, three models: comparison of land-use/transport policy simulation models for Dortmund.* Transport Reviews, 1991. **11**(2): p. 107-129.
65. Wegener, M., *Land-Use Transport Interaction Models*, in *Handbook of Regional Science*, M. Fischer and P. Nijkamp, Editors. 2014, Springer: Berlin, Heidelberg. p. 741-758.