POLICY BRIEF

Land Use Mix

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Program Description

This project reviews and summarizes empirical evidence for a selection of transportation and land use policies, infrastructure investments, demand management programs, and pricing policies for reducing vehicle miles traveled (VMT) and greenhouse gas (GHG) emissions. The project explicitly considers social equity (fairness that accounts for differences in opportunity) and justice (equity of social systems) for the strategies and their outcomes. Each brief identifies the best available evidence in the peer-reviewed academic literature and has detailed discussions of study selection and methodological issues.

VMT and GHG emissions reduction is shown by effect size, defined as the amount of change in VMT (or other measures of travel behavior) per unit of the strategy, e.g., a unit increase in density. Effect sizes can be used to predict the outcome of a proposed policy or strategy. They can be in absolute terms (e.g., VMT reduced), but are more commonly in relative terms (e.g., percent VMT reduced). Relative effect sizes are often reported as the percent change in the outcome divided by the percent change in the strategy, also called an elasticity.

Summary

Strategy Description

Land-use mix (LUM) or mixed-use development can be defined as the practice of accommodating more than one type of function within a building, a set of buildings, or a specific local area. These functions can be delineated in categories such as residential, office, retail, and personal services, as well as parks and open space.

Widely advocated as a key principle of sustainable development, LUM is central to such major urban planning and design concepts as smart growth, New Urbanism, and transit-oriented development (Manaugh and Kreider, 2013). Measured at the neighborhood scale, LUM is considered necessary for or even implicitly equivalent to *local accessibility*; by bringing trip origins and destinations closer together, mixed-use neighborhoods and buildings can facilitate walking, biking, and transit use, while shortening car trips, in turn reducing vehicle miles traveled (VMT) and greenhouse gas emissions (Ewing and Cervero, 2010).

The most common LUM measure employed in research is the entropy index, which measures the balance of land uses in a neighborhood based on the variety of different land use types and level of mixing compared to an ideally balanced mix (often considered for the urban area as a whole). Entropy values range from 0 (one land use only), to 1 (all land-use categories proportionally represented as in the benchmark measure).

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Researchers have not reached consensus about a "correct" or optimal geographic scale for measuring LUM impacts, and LUM can affect travel behavior across multiple scales, from local to regional. Few studies have experimented with scale variation in LUM measurement, but the studies that have done so find different effects at different scales.

Measurement of LUM has come under criticism for the widespread inconsistencies in methods seen across studies, including in scale and measurement of boundaries employed, in the way land uses of interest are identified and categorized, and in the computation formula employed (see Manaugh and Kreider, 2013). Some scholars argue that the basic problem with LUM modeling traces to a lack of adequate theoretical foundations, and empirical validity testing and comparison, of results using alternative measures (Manaugh an Kreider, 2013; Song et al., 2013; Gehrke and Clifton, 2019). These scholars question the basic starting assumption that greater "balance" of land use types in any given locale constitutes a better condition than a less balanced locale. Few studies, however, go beyond evaluating diversity and balance of general land use types in a local area to also consider the relative attractiveness (quality), complementarity, and sufficiency of precise land uses. But while current LUM modeling may have significant shortcomings, the development and application of more sophisticated measures can require significant commitment of resources, such as for fine-grained data collection.

Behavioral Effect Size

A summary of findings from each of 14 individual studies that estimate the effect of LUM on VMT is presented in Table 1 (pp. 9–11), at the end of this report. The reported elasticities range widely, from a 0.0 to 0.35 percent decrease in VMT for each 1 percent increase in land-use mix (or an elasticity of 0.0 to -0.35). The discrepancies in results reflect in part the above-noted inconsistency in LUM measurement across studies. To narrow down findings to a comparable set of studies, we can consider results from only those studies that employed a LUM entropy index, and which followed the recommended approach of measuring land use mix within dynamic "sliding" buffers (measured for a radius of x distance from each study observation, e.g., a household or residence), rather than within fixed, bureaucratic boundaries, such as Census tracts. Among the 5 studies in Table 1 that meet this description, the range of reported elasticities, with one exception, was between -0.04 to -0.10. These findings correspond closely to results from two widely cited meta-analyses of multiple land use-transportation studies from across the world, conducted by Ewing and Cervero (2010) and Stevens (2017); the first of these two analyses found that a 1 percent increase in land-use mix results in an average VMT decrease, across studies considered, of 0.09 percent, while the second found an average decrease of 0.03 percent.

Co-benefits and Synergies

Perhaps the main co-benefit of mixed-use development is the encouragement of walking, bicycling, and use of transit and shared mobility services such as bikeshare. In addition to reducing vehicle emissions, walking and cycling as modes of transport are important from a public health perspective. Considering results from eight studies, Ewing and Cervero (2010) estimated that on average, walking trips increase 0.15 percent for each 1 percent increase in land-use entropy.

Compactly built, mixed use, and walkable neighborhoods are also critical for transit to succeed (Suzuki and Cervero, 2013). For transit trips, Ewing and Cervero (2010) estimate the elasticity of LUM as a 0.12 percent increase in transit trips for a 1 percent increase in LUM. Transit usage is found to increase when both trip origins and destinations are located near transit stops, meaning that mixed uses along transit corridors and in multiple station areas can facilitate more ridership (Nasri and Zhang, 2019; Cui et al., 2022; Wu et al., 2023).

Equity Considerations

Since low-income people tend to drive less and use transit and walk more than higher-income people, they benefit from local accessibility facilitated through compact and mixed land uses. When walk access is measured in terms of physical street connectivity between origins and destinations, the research points to an overall overlap between highly walkable neighborhoods and areas where socially vulnerable (SV) populations live, reflecting historical conditions and events, such as redlining and exclusionary zoning, which constricted many SV households to urban core neighborhoods. However, if walkability is considered not just as physical access, but in relation to other micro-level and personal considerations including street greenery, sidewalk conditions, and other safety factors including exposure to crime threats, then SV populations, even when living in walkable neighborhoods, do not experience equitable conditions (Koschinsky et al., 2017; Conderino et al., 2021; Bereitschaft, 2023). Some research finds furthermore that SV populations are disadvantaged in accessibility for certain trip purposes, including trips to shopping and supermarkets (Grengs, 2015).

Strategy Description

Land-use mix (LUM) or mixed-use development can be defined as the practice of accommodating more than one type of function within a building, a set of buildings, or a specific local area. These functions are delineated to include categories such as residential, office, retail, and personal services, as well as parks and open space.

LUM is widely advocated as a key principle of sustainable development, central to such major urban planning and design concepts as smart growth, New Urbanism, and transit-oriented development (Manaugh and Kreider, 2013). LUM measured at the neighborhood scale is considered necessary for or even implicitly equivalent to *local accessibility*; by bringing trip origins and destinations closer together, through policies such as mixed-use zoning, mixed-use neighborhoods and buildings can facilitate walking, biking, and use of transit and shared mobility options such as bikeshare, while shortening car trips and in turn reducing VMT and greenhouse gas emissions.

Research indicates that land use mix is especially influential on local travel through its impact on mode choice for local, generally non-work trips (Saelens and Handy, 2008; Gehrke and Clifton, 2014). LUM has been found to be a more significant factor affecting non-commuting trips than commuting trips (Ding et al., 2017). By contrast, *regional-scale accessibility* (further discussed in the *Regional Accessibility Policy Brief*), often measured as access to jobs, is generally associated with commute trips by auto or transit, the modes most capable of facilitating longer-distance travel in metro areas.

Reflecting its importance for local accessibility, LUM information is central to the calculation of established measures of local accessibility, such as Walk Score, a metric widely used to evaluate effects of the built environment on walking behavior. Walk Score combines information on cumulative opportunities (available destinations), development density, and travel network connectivity using a gravity-based approach, which discounts destinations up to 2,400 meters based on their distances (Lussier-Tomaszewski and Boisjoly, 2021).

Various measures have been used to capture the amount of land-use mixing at the neighborhood scale, including:

- Variety and balance of land-use types within a neighborhood or buffer zone (entropy or dissimilarity indices);
- Ratio of jobs to residents at the neighborhood level (e.g., census tracts, census block groups, or ¼ mile radius areas); and

- Number of destinations of a particular type (e.g., grocery stores) within a given distance of residences.

The LUM measure used most commonly in research is the entropy index, which measures the balance of land uses in a neighborhood based on the variety of different use types and the level of mixing compared to an ideally balanced mix (often considered for the urban area as a whole). Entropy values range from 0 (one land use only), to 1 (all land-use categories proportionally represented in reference to the benchmark used).

The basic equation for land-use entropy is:

$$ENT = -\frac{\sum_{j=1}^{N} P^j \ln(P^j)}{\ln(N)}$$

where ENT is the entropy value, N is the number of different types of land use in the region of interest, and P^j indicates the number of parcels or grids of *j* land use type. The entropy value ranges from zero (completely homogeneous land use) to one (perfectly balanced among all uses). Optimally, the value is normalized by dividing the measure for each unit of land by the log of the number of possible land use types measured across the wider area of interest, such as the city as a whole (Hajna et al., 2014).

Scale of measurement (size of the geographic unit of analysis) is a critical concern given that most trips extend beyond localized neighborhood boundaries. Ewing et al. (2011) found that even for large-scale urban mixed-use developments (ranging in size from 100 to 400 acres), the average internal trip capture rate was 18%, meaning that approximately four-fifths of trips starting from these locations ventured outside.

Researchers have not reached consensus about a “correct” or optimal geographic scale for measuring LUM impacts, because LUM can affect travel behavior across multiple scales. LUM measured at wider scales can logically be expected to be more diverse than LUM measured at smaller scales. LUM impacts for rural areas, which are often highly car-dependent, may especially require consideration at wider-than-local scales.

Some research has found different LUM effects at different scales. For example, Chatman (2008) found that activity density measured at smaller radii were more highly correlated with walking frequency than with auto use frequency, but the opposite effect was observed at larger radii. Zhang and Kukadia (2005) found that an entropy index produced significant results only when measured at a ½-mile grid size or larger, while Gehrke and Clifton (2014) found that measuring land use mix at the tract level provided the best fit. However, few studies have experimented with scale variation in LUM measurement (Gehrke and Wang, 2020).

Entropy measures of LUM have come under increasing criticism among scholars. Researchers often use jobs by type as a proxy for land uses (e.g., retail versus office employment), because this approach makes entropy indexes easy to compute, such as from Census data. But widespread inconsistencies in methods are evident across studies, including in scale and measurement of boundaries employed, in the way land uses of interest are identified and categorized, and even in the computation formula employed (see Manaugh and Kreider (2013) for an in-depth discussion about these concerns).

Disparate methods and findings across LUM studies make it difficult for scholars and practitioners to interpret results. Some scholars argue that the basic problem with LUM modeling traces to a lack of adequate theoretical foundations, and empirical validity testing, of alternative measures (Manaugh and Kreider, 2013; Song et al., 2013; Gehrke and Clifton, 2019). These scholars question the basic starting assumption that greater “balance” of land use types in any given locale constitutes a better condition than a less balanced locale. Few studies go beyond evaluating diversity and balance of land use types in a local area to also consider the relative attractiveness (quality), complementarity, and sufficiency of precise land uses – e.g., in considering the importance of one grocery store located nearby for inducing walking trips, as opposed to considering lumped-up retail as a broader category measured at a wider scale. Some scholars argue that advocating for a uniform dispersal of similar land uses throughout an urban area is neither feasible nor desirable, because organizing some land uses hierarchically can better facilitate transport efficiency (Mouratidis, 2024).

Thus, even though LUM is widely viewed as a critical aspect of the built environment for influencing travel behavior, given its role in enhancing accessibility through proximity, consensus is lacking on how it should be measured and optimized. In response to such concerns, some scholars argue for improving LUM modeling through more careful measurement of quality, sufficiency, intensity, complementarity, and integration of proximate land uses, rather than just considering aggregate balance among broad land use types (ibid; Elldér et al., 2022). Gehrke and Clifton (2019) developed and employed a novel LUM measure of this sort aimed at capturing, in addition to diversity, also fine-grained intensity and spatial integration of land use types, and found that their measure was a significantly more effective predictor of walk mode choice and home-based walk trip frequency, when operationalized at three geographic scales, than a traditional entropy-based index. However, while current LUM modeling may have significant shortcomings, the development and application of more sophisticated measures often entails a significant commitment of resources, such as for data collection at a fine-grained scale.

Other measures of land-use mix employed in research besides the entropy index include dissimilarity indexes, defined by Cervero and Kockelman (1997) as the fraction of abutting parcels or grids with different land uses from the parcel or grid of interest, with possible values ranging from zero (all abutting uses the same as the central area) to one (all abutting uses different from the central area). Cervero and Kockelman (1997) consider that an advantage of the dissimilarity index over an entropy index is its its usefulness in studying finely grained land use mixing – down to the parcel level. Those aspects also mean this approach can be laborious to employ, helping explain why relatively few studies do so.

For further description and discussion of these and additional LUM measures, see Song et al. (2013) and Iannillo and Fasolino (2021).

Strategy Effect

Theoretical concerns and inconsistencies in measurement and definition of LUM, such as those described above, mean that LUM and local accessibility remain “elusive” concepts whose precise impacts are hard to discern (Vale et al., 2016; Manaugh and Kreider, 2013). However, most research studies evaluating the impact of LUM on VMT, measured locally using an entropy index, have found small but still significant effect sizes.

Behavioral Effect Size

Ewing and Cervero (2010) used meta-analysis to determine, based on findings from a range of high-quality studies from across the world, that a one percent increase in land-use mix results in an average VMT decrease of 0.09 percent, representing the VMT benefit that might be expected from policies designed to increase mixing of land uses. A second meta-analysis by Stevens (2017) found an average VMT decrease of 0.03 percent across the studies considered from a one percent increase in LUM.

A summary of the findings from each of 14 individual studies that estimate the effect of LUM on VMT is presented in Table 1. Eleven of the studies were included in the Ewing/Cervero and Stevens meta-analyses; these were studies conducted in North America after 2000. An additional three studies shown in Table 1 were not included in the meta-analyses: those from Salon et al., 2015; Zhang and Zhang, 2018; and Lee and Lee, 2020.

The elasticities estimated for LUM from the studies shown in Table 1 indicate a wide range of effect sizes, from a 0.0 to 0.36 percent decrease in VMT for each 1 percent increase in LUM (or an elasticity of 0.0 to -0.36). The wide range of results reflects the inconsistency in LUM measurement methods discussed above.

Most of the studies shown in Table 1 employ an entropy index, but other discrepancies are evident. One clear discrepancy is in whether the studies utilized fixed, bureaucratic boundaries, such as Census tracts, in which LUM entropy index values were calculated, or instead used dynamic "sliding" buffers (measured for a radius of x distance from each study observation, e.g., a household or residence). Sliding buffers are recommended by scholars as a more precise and consistent measure of LUM surrounding particular households than fixed bureaucratic boundaries. More than half the studies shown in Table 1 used fixed, bureaucratic boundaries to measure LUM in the areas in which sample households resided.

Except for one extreme outlier (the study on Montreal by Zahabi et al., 2015), the studies from Table 1 that employed a LUM entropy index, measured using dynamic buffers, found elasticities that ranged from -0.04 to -0.10, a fairly close range; however, even this subset cannot be considered strictly comparable because the studies did not employ the same land use categories in constructing the index. Another discrepancy, for those studies that utilized dynamic buffers, concerns the size of buffers used, which range in the studies shown from ¼ mile to 1 mile.

One notable large-sample study from California, by Salon (2015), calculated the effect on work- and non-work VMT of a LUM entropy index measured at the Census tract level, while also controlling for four other commonly tested built-environment variables (density, destination accessibility, distance to transit, and street design), as well as for self-selection bias (which occurs when people choose a residential location based on their transportation preferences). This study found an elasticity of -0.05 for non-work trips and -0.07 for commute trips, similar to the findings just described from the studies which used an entropy index with sliding buffers.

Co-benefits and Synergies

Perhaps the main co-benefit of mixed-use development is the facilitation of walking, bicycling, and transit use. Studies have generally shown that the impact of LUM is greater for inducing walking trips than for VMT reduction; Ewing and Cervero (2010) estimate that on average, walking trips increase 0.15 percent for each 1 percent increase in land-use entropy.

In addition to reducing vehicle emissions, walking and cycling as modes of transport are important from a public health perspective. Increased physical activity is associated with various positive outcomes, such as reducing obesity (Nieuwenhuijsen, 2020). The health benefits of walking and cycling can benefit rural, not just urban households, for example in providing access to recreational areas.

While cities with low motorized mobility rates are associated with health gains (e.g., diabetes, cardiovascular disease, respiratory disease, and lifespan), some trade-offs can occur in terms of greater road trauma for cyclists and pedestrians (Stevenson et al., 2016). This situation points to the need for policies to ensure the provision of safe walking and cycling infrastructure.

Benefits of LUM relate not just to physical activity. Destination accessibility has also been associated with social cohesion, for example (Mombelli et al., 2025). Proximity to supermarkets and health food stores is associated with improved diet patterns and weight status (Popkin et al., 2005; Cummins and Macintyre, 2006). Low-income neighborhoods, however, often lack access to high-quality resources.

Compactly built, mixed use, and walkable neighborhoods are also critical for transit to succeed (Suzuki and Cervero, 2013). For transit trips, Ewing and Cervero (2010) estimate the elasticity of LUM as a 0.12 increase in transit trips for a 1 percent increase in LUM. Transit usage is found to increase when both trip origins and destinations are located near transit stops, meaning that mixed uses along transit corridors and in multiple station areas can facilitate more ridership (ibid; Nasri and Zhang, 2019; Cui et al., 2022; Wu et al., 2023).

Equity Considerations

Since low-income people tend to drive less and use transit and walk more than higher-income people, they benefit from local accessibility facilitated through compact and mixed land uses.

Some research has directly investigated whether socially vulnerable (SV) populations have equitable access to walkable and transit-accessible neighborhoods (Koschinsky et al., 2017; Conderino et al., 2021; Bereitschaft, 2023). When walk access is measured in terms of physical street connectivity between origins and destinations, the research points to an overall overlap between SV and highly walkable neighborhoods in many cities, albeit with significant variability. This finding reflects the fact that due to historical conditions and events, such as redlining and exclusionary zoning, many SV households live in urban core neighborhoods.

However, if walkability is considered not just as physical access, but in relation to other salient micro-level and personal considerations including street greenery, sidewalk conditions, and other safety factors including exposure to crime threats, then SV populations, even when living in walkable neighborhoods, do not experience equitable conditions (ibid). Furthermore, some research finds that while socially vulnerable groups, including African Americans, Hispanics, low-income households, and households in poverty, experience greater physical accessibility than more privileged groups for several trip purposes, including convenience stores, childcare facilities, religious organizations, and hospitals, vulnerable groups are disadvantaged in accessibility to shopping and supermarkets (Grengs, 2015).

Confidence in Evidence Quality

The studies shown in Table 1 have various methodological discrepancies described earlier, which help explain the wide variance in results. For that reason, we focused on findings from studies that used similar measurement techniques (entropy indexes and sliding buffers).

All of the studies in Table 1 used models that control for the effects of other variables that could impact VMT, in particular individual and/or household demographic characteristics such as income, household size, and automobile ownership. As delineated in Table 1, the studies also controlled for various other aspects of the built environment, such as development density, street design, and transit access, usually measured at the local neighborhood scale. In addition, these studies use individual and household-level data rather than aggregated data for geographical areas. These qualities strengthen the reliability of the evidence.

Few of the studies shown in Table 1 considered wider-than-local land use characteristics. Most of the studies measured LUM effects across urban and metro areas without distinguishing how impacts vary between highly urban, suburban, and rural contexts. Furthermore, few of the studies considered land use factors measured at a regional or sub-regional scale. Research on travel impacts increasingly considers built environment variables measured at regional and sub-regional scales (e.g., centeredness, population-weighted density, jobs-housing balance, and job accessibility within a certain time or distance), in addition to locally measured ones. While most of the studies shown in Table 1 controlled for “destination accessibility,” generally measured at a sub-regional scale as job access within a certain time or distance, they did not control for a range of other region-scale development factors.

Only a few of the studies included in Table 1 account for residential self-selection. Self-selection occurs when people choose a residential location based on their transportation preferences. For example, people who wish to drive less may move into dense, mixed-use neighborhoods that allow them to use their car less or use non-car modes of transportation more easily. Studies that do not account for self-selection may overstate the effect of land-use mix on VMT. However, research has indicated that self-selection bias does not pose an insurmountable hurdle to establishing viable results. Cao, Mokhtarian and Handy (2009) reviewed 38 empirical studies that controlled for self-selection, determining that virtually all exhibited significant built environment impacts even after controlling for self-selection. However, it seems likely that if residential self-selection were accounted for, the effect sizes noted in Table 1 would be lower. This factor introduces additional uncertainty into how much of the reported effects from previous studies can be attributed to the land-use mix alone.

Table 1. Relationship of VMT and Land Use Mix[1]

Study	Survey data location & year; number of observations; dependent variable	Specification of diversity (land use mix, a.k.a. LUM) measure	Elasticity (change for 1% increase in LUM)	Other "D" variables included in study as independent variables, measured locally				Control for self-selection?
				Density	Destination accessibility	Distance to transit	Street design	
Boarnet et al., 2004	Portland, OR, 1994; 6,154 observations; non-work daily VMT per person	Density of retail and total employment at tract level	All jobs = 0.03; retail = -0.02	x	x		x	No
Chapman & Frank, 2004	Atlanta, 2001-02; 8,069 HH observations; VMT per person	LUM entropy index within 1 km for residential, commercial, and office	-0.04	x			x	No
Chatman, 2008	San Diego and SF-Oakland-San Jose regions, 2003-04; 527 observations; non-work VMT per person	Number of retail jobs/ developed acre	-0.19				x	No
Ewing et al., 2013	Six US regions, 1991 to 2001; 35,877 trip ends to/from 239 mixed-use developments (MXDs); per person VMT for work/nonwork	LUM entropy and job/population balance w/in MXD[2]	For LUM, 0.0 for both work and non-work trips; for job-population balance, 0.0 for work trips, -0.08 for other trips		x		x	No
Ewing et al., 2015	15 US regions (inc. Sacra-mento), 2005 to 2012; 62,011 observations; VMT per HH	Job-population balance w/in 1/4 mi; LUM entropy w/in 1 mi for uses as per Ewing et al., 2013	job-population = -0.03; entropy = -0.10	x	x		x	No
Frank et al., 2009	King County, Puget Sound, 2006; 2,697 observations; VMT per household	LUM entropy index within 1 km for SF/MF residential; retail; office; civic/educ; and entertainment	-0.04		x	x	x	No

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[1] Abbreviations: HH, household; LUM, land use mix.
[2] LUM = entropy calculation within MXD is for net acreage in residential, commercial, industrial, and institutional

Table 1 (continued). Relationship of VMT and Land Use Mix

Study	Survey data location & year; number of observations; dependent variable	Specification of diversity (land use mix, a.k.a. LUM) measure	Elasticity (change for 1% increase in LUM)	Other "D" variables included in study as independent variables, measured locally				Control for self-selection?
				Density	Destination accessibility	Distance to transit	Street design	
Heres-Del Valle & Niemeier, 2011	California, 2000-01; 7,666 HH observations; HH daily VMT	Business to housing ratios by zip code	-0.04[3]	x		x		Yes
Kuzmyak et al., 2006	Baltimore metro area, 2001; 2,707 observations; daily weekday VMT per HH	LUM entropy and walk opportunities indexes, both within 1/4 mi[4]	entropy = -0.09; walk opportunities = -0.10		x			No
Lee & Lee, 2020	2009 National Household Travel Survey (NHTS) data for 2009 for the 121 largest urban areas in the US; 56,373 observations; annual household VMT	LUM entropy index for Census tract[5]	-0.03	x	x	x	x	No
Nasri & Zhang, 2012	Six US metro areas, 2006 to 2009; 22,904 observations; per person VMT	LUM entropy index for TAZ/tract for residential; service; retail; other LU	-0.06	x	x		x	No
Salon, 2015	California, 2000 to 2013; 60,346 observations; weekday nonwork VMT; daily one-way commute VMT	LUM entropy index at tract level for homes and jobs by industry (retail, office, industrial, public sector)	non-work trips = -0.05; commute trips = -0.07	x	x	x	x	Yes

[3] Elasticity = -0.04 on its own, without density or transit access, but e= 0.05 (positive sign) with density included; significant only when density not included

[4] Entropy index based on proportions of land for residential; commercial; public; offices and research sites; industrial; and parks and rec. Walk opportunities index is a distance- and importance-weighted measure of available destinations

[5] LUM entropy index is for residential, commercial, industrial, and offices (for which employment by industry is used as a proxy of non-residential land use and number of workers by residence as a proxy for residential land use)

Table 1 (continued). Relationship of VMT and Land Use Mix

Study	Survey data location & year; number of observations; dependent variable	Specification of diversity (land use mix, a.k.a. LUM) measure	Elasticity (change for 1% increase in LUM)	Other "D" variables included in study as independent variables, measured locally				Control for self-selection?
				Density	Destination accessibility	Distance to transit	Street design	
Zahabi et al, 2015	Montreal area, 2007; 147,574 observations; "car distance"	LUM entropy index in 500x500m buffer[6]	-0.36	x		x		Yes
Zhang et al., 2012	Six US metro areas, 2006 to 2009; 22,904 observations; per person VMT	LUM entropy index for TAZ/tract for residential; service; retail; other LU	Baltimore = -0.08; Seattle = -0.16; Virginia = -0.01; Washington DC = -0.17	x	x		x	No
Zhang & Zhang, 2018	Austin, TX, 2005–2006; 975 observations; daily per person VMT	LUM entropy index (categories not described) for planning areas	No pref = -0.35; With pref = -0.55[7]	x	x		x	Yes

[6] LUM entropy index for residential; commercial; government; resource/industrial; and parks and recreation, with water and open space excluded

[7] The study employed survey information on residential preference as a control for self-selection distinguishing respondents who indicated preference for access and neighborhood amenities (including safety) (= self-selection group) vs. others (= non-self-selection group).

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