Using urban migration flows for non-market amenity valuation*

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Abstract

Do migration flows tell a richer story about amenity preferences than population stocks? Economists often use a household's residential location as a revealed preference for place. If a large stock of people reside in a location with low wages and expensive housing costs, local amenities must be abundant or migration costs high. This paper studies what a household's previous location - their residence during the migration decision - can add to our understanding of tastes for regionally-varying environmental amenities. We show evidence of heterogeneous migration propensities across space and find a correlation between the "stickiness" of a place, and its quality of life. This motivates our development and estimation of a generalized national-level sorting model that accommodates heterogeneity in migration costs across origins. Our demand model bears a gravity-like structure. We leverage this structure by identifying our key parameters from variation in spatial differences of migration flows across origins and destinations. As a result, this model lives in a single temporal cross-section; notably, our flow approach produces credible estimates without relying on temporal variation. In our empirical application, we estimate our model on a national sample of US households who sort amongst metropolitan statistical areas, and find marginal willingness to pay values for climate amenities and air quality.

Keywords: migration, residential sorting, nonmarket valuation, air quality, climate, gravity
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1 Introduction

Do migration flows tell a richer story about amenity preferences than population stocks? Economists often use a household's residential location as a revealed preference for place. If a large stock of people reside in a location with low wages and high housing costs, local amenities must be plentiful or migration costs high. This paper studies what a household's previous location - their residence during the migration decision - can add to our understanding of tastes for regionally-varying environmental amenities.

To answer this question, we construct a national equilibrium sorting model. These models have become a popular methodological alternative to the Rosen-Roback-Albouy hedonic framework (1974; 1982; 2016). In the conventional hedonic approach, household preferences are implicitly captured by equilibrium wages and housing prices. In the sorting framework, households' trade-offs between wages, housing, and amenities are made explicit: households select their residential location from a discrete menu of metropolitan statistical areas (MSAs) based on the locale's characteristics and their respective budget constraint. Each location decision reveals household preferences, from which we can infer marginal willingness to pay (MWTP) for an amenity based on Tiebout's (1956) logic. And by modeling the household location choice directly, this approach can relax assumptions of free mobility, thereby allowing for the incomplete capitalization of amenities into wages and rents.

We build from this standard sorting framework, but innovate by modeling the role that a household's pre-choice MSA location (henceforth, a household's *origin*) plays in its migration decision. This distinction proves economically intuitive in a world where migration costs may vary by origin: some *places* are harder to leave than others. This notion underlies well-known federal relocation programs like Moving to Opportunity, but certainly applies at wider geographic scales. Recent labor and urban economics research explaining differences in domestic US migration patterns has underlined these systematically-varying rates of "stickiness" or "churn" across cities. We highlight evidence of these spatially-heterogeneous migration frictions in our data and argue they may be important when inferring non-market amenity values.

More broadly, our modification of the standard sorting model yields a gravity-like estimation structure that emphasizes the convenient link between demand estimation methods and classical economic models of migration. This structure is econometrically substantive: for a given destination MSA, we observe meaningful variation in the size of incoming migration flows from different origin MSAs. Our reliance on this alternative source of preference revelation - in essence, a repeated cross-section of observed population shares selecting a given destination - provides novel identification of our structural parameters of interest. In the era of big, real-time data, this turn to spatial differences in lieu of temporal differences is meant to be provocative: can we credibly measure MWTP using a single temporal cross-section?

Through the proposed reliance on origin and destination for preference revelation, we revisit the estimation of MWTP for two well-studied regional environmental amenities: climate and air quality. In spatial equilibrium, under the common assumption of linear-in-variables utility, we derive MWTP for an amenity as a familiar ratio of parameterized marginal utilities. We take the model to data, relying on a publicly-available, cross-sectional database constructed from 2012-2016 Census migration flow estimates, American Community Survey (ACS) microdata, and various MSA-level measures of natural and anthropogenic amenities.

As an illustrative example of our model's divergence from the conventional national sorting literature, our empirical analysis begins with a parsimonious representative agent model that only uses aggregated migration flows and location characteristics. Leveraging econometric tools from the trade and migration literatures, our gravity-like estimates produce two indices of structural interest: MSAs' propensity for migration ("push" measures) and overall attractiveness or quality of life ("pull" measures). We highlight these rankings, finding that smaller Rust Belt cities and retiree-friendly cities in Florida have the stickiest populations, while college towns, military bases, and smaller cities in the Western states have the most population churn. Our quality of life index foreshadows our main valuation findings: many Sun Belt cities rank amongst the most attractive, and smaller cities in the Midwest and Rust Belt as among the least attractive.

Next, we proceed to our main empirical exercise, extending this aggregate model to the household-level by incorporating a 5-year sample of ACS microdata to model individual households' location decisions. We link the gravity estimation structure of our aggregate analysis to the two-stage, microdata-driven approaches used in previous random-utility-based national sorting models. This link allows us to bifurcate households' deterministic utility into a mean origin-destination specific component and a household-specific component. As a result, our household-level model captures richer economic heterogeneity: household income and housing expenditures are modeled destination-by-destination, while tastes for amenities and the household's costs of migration vary based on observable demographics.

We estimate first-stage household-level parameters by maximum likelihood, nesting a contraction mapping in the procedure to match moment conditions. The micro-model's predicted migration flows across space are equalized to observed flows provided by the Census aggregate-level data. In the second stage of the model, we run instrumental variable regressions of average origin-destination indirect utility on destination amenities, while controlling for origin-conditions with fixed effects. This two stage approach allows us to account for both spatially-heterogeneous migration frictions and endogenous amenities in a tractable fashion.

In our preferred baseline IV results, we find that a household earning close to the median national income level has an average MWTP of \$818 for a 1μg reduction in daily PM2.5 exposure, \$1,647 for a one degree (Celsius) increase in average winter temperature, and \$846 for for a one degree decrease in average summer temperature. Notably, this specification models utility from income using a semi-parametric linear spline; our results suggest the marginal utility of income diminishes more slowly than a conventional log specification would imply. We also study heterogeneity in several dimensions. Older, younger, and more educated households exhibit stronger tastes for climate amenities. Preferences also differ by origin, with results suggesting varying degree of previous taste-based sorting across amenities.

Contribution to literature

This paper's approach to nonmarket valuation augments practitioners' methodological toolkit when data on residential migration flows are available. Thus, our principal contribution is a fresh marriage of revealed preference logic to a rich literature on migration that studies population flows across space.[1] Our model builds on static spatial equilibrium notions, but relaxes several key assumptions inherent to the continuous hedonic approach (Cropper et al, 1993; Sinha et al, 2019). The cost of doing so is the imposition of more conspicuous structure on household preferences.

Our work adopts much from national sorting models that value regionally-varying environmental amenities. Cragg and Kahn (1997) use US census data to model households' choice of state; they then infer MWTP for climate amenities, noting that their estimates are substantially larger than those from hedonic models. In now-seminal work, Bayer et al (2009) show theoretically and empirically that moving costs help explain the wedge between the true MWTP for MSA-level air quality and the hedonic value capitalized into national housing prices and wages. Their identification strategy relies on long-run first-differences and an IV for air pollution. Sinha et al (2018) incorporate random coefficients into a purely cross-sectional version of the Bayer et al framework, methodologically updating the earlier findings by Cragg and Kahn. In our empirical application, we reexamine the amenity values of both climate and air quality with data from a more recent period.

Our paper also adds to a growing body of work that methodologically extends the sorting framework for amenity valuation. Bishop (2007) estimates a dynamic national sorting model, noting that estimates of MWTP may be biased if households are forward-looking and make location decisions based on expectations of future amenities, wages, and prices. Hamilton and Phaneuf (2015) estimate a national sorting model that allows for a two-stage household choice of city and neighborhood. By jointly modeling between- and within-MSA sorting, they account for potential substitution patterns at the local level while inferring non-market value at the MSA level. Lee (2017) uses RUM-based simulation evidence of household-level heterogeneity in moving costs to explain national patterns of environmental injustice. In a hypothetical migration setting, Kosar et al (2020) use stated preference methods to infer MWTP for several amenities of common interest in the urban and environmental literatures. The results from their hypothetical choice experiments imply substantial and systemic household-level heterogeneity in moving costs. The joint message from this growing set of papers is clear: when behavioral complexities are overlooked, true MWTP for air quality, climate, or other amenities can be misstated.[2] Our work delivers a similar message. Household origin can play a meaningful role in explaining migration patterns, and therefore merits inclusion in the discrete choice framework.

[1]There is a wealth of classic environmental/regional/urban economics work that explores US-centric migration determinants using models with underlying similarities to ours. None make the step to nonmarket valuation, as far as we know. Greenwood (1997) provides an overview of this research.

[2]Diamond (2016) and Bieri et al (2020) are also concerned with complexities in national sorting behavior, though aren't focused on the valuation of specific amenities. The former fully endogenizes MSA-level amenity indices in a general equilibrium sorting model, while the latter builds from the model's key pieces to carefully measure *aggregate* US amenity expenditures.

Finally, we contribute to the deep and diverse social science literature that explains migration patterns through the use of gravity-like models.[3] Our work builds from random-utility micro-foundations that have recently reestablished the gravity model as a structural workhorse in the study of international migration patterns. Beine et al (2016) summarize this resurgence and describe best practices for estimating gravity models of migration with aggregate flow data. Our approach to including microdata into this gravity-like migration model varies from previous work. Hunt and Mueller (2004), Bertoli et al (2013), and Plantinga et al (2013) estimate household-level migration models using a nested logit framework to capture a stay/go decision hierarchy: a household's origin location falls in one nest and all other potential destinations reside in another. Neither paper values local amenities. In contrast, the sorting model we propose defines each origin MSA as a separate "market", thus serving as a more direct micro-analogue to Beine et al's baseline gravity framework. In a similar spirit to work by Druckenmiller and Hsiang (2019), we view this repeated cross-section of location choices as an opportunity to test the credibility of parameter estimates derived from spatial differences.

Organization

Section 2 of this paper describes stylized facts that motivate our model, while highlighting the publicly-available data on which the following analyses rely. Section 3 lays out theoretical foundations, underlining key differences from previous national sorting work. Section 4 discusses estimation and stylized results from an illustrative aggregate-data model. Section 5 discusses the estimation and identification strategies for our full model, incorporating household microdata. Section 6 discusses empirical results from our nonmarket valuation application. Section 7 concludes.

2 Context and data

A household's decision to move reflects the overcoming of locational inertia. This proves to be of crucial import when estimating the determinants of location choice. In a world without moving costs, the spatial distribution of housing prices and wages tell a rich story about the monetary value of a place's characteristics (Roback, 1982). In a less stylized world, the psychological and familial frictions of human ties to a specific place render these stories inapplicable; households stay, despite economic opportunity and amenity elsewhere. The unobserved costs of moving may overwhelm the observable benefits, and researchers therefore struggle to learn how households value spatial characteristics of other localities.

The national sorting approach adapts to this behavioral phenomenon and models accordingly. Nearly all previous discrete choice measures of household WTP for regional amenities have conditioned on demographic-varying measures of moving costs *away from birthplace*. This assumes that the cost

[3] Applications of gravity-like models pop up in several fields beyond migration where flow data abound: trade, transport, network analysis, and beyond. Though some in the migration and transport literatures have pivoted away from gravity models for purely predictive work - see, for instance, the radiation model - the gravity model's parametric structure remains highly tractable for our goal of amenity valuation.

of leaving *any* birthplace is homogeneous. The logic is simple: it is costly to choose a location further from your birthplace, perhaps more so if your family includes children or multiple full time wage earners. But these measures may still miss the subtlety of place: some cities are "stickier" than others. For example, several lines of research suggest that the psychological costs of leaving a former industrial MSA in the Rust Belt may differ from the costs of leaving a Sun Belt MSA. If this is the case, a population-stock-based description of locational determinants will miss details that could be captured with flow data.

Figures 1 and 2 illustrate patterns in national data to support this assertion. Figure 1 shows the near-linear scatterplot of annual average out-migration and in-migration rates across the MSAs that we study from 2012-2016. A study of population stocks over time can tell us about population growth or decline rates over this period, but it would mask the fact that there is rich heterogeneity in inflow *and* outflow rates. Places that attract a relatively large number of people are also losing a lot of people. Some of this is mechanical: both city size and the characteristics of the city play a role. Figure 2 plots each MSA's annual churn ratio[4] from 2012-2016 against the percentage of initial population born in-state. If we differentiate by whether the MSA has a large university-related or military-related population (both of which may breed higher turnover naturally), the negative correlation between % of people born nearby and the population's dynamism is striking. Stickier places do not appear to be drawing people from elsewhere, and places with a lot of churn seem less likely to have a population with high moving costs.

Urban and labor economists have shown recent interest in why locations become "sticky". Papers like Glaeser and Gyourko (2005), Gyuorko et al (2013) and Ganong and Shoag (2017) tell a market-driven story of the phenomenon. The durability of housing makes urban decline gradual in depressed cities: a large available stock of housing pushes prices down while the local economy slows. Local residents stay and wages stagnate. Meanwhile, land supply restrictions are pervasive in fast-growing, high-wage cities in the US: housing costs explode as local demand exceeds the constrained supply. Together, these market mechanisms conspire to make migration costly and unattractive to households in depressed areas, especially those with less-skilled workers. But this does not necessarily explain the low migration from sticky places to alternative non-"superstar" cities, nor the low in-migration rates to sticky places.

Coate and Mangum (2019) approach this shortcoming by formalizing the notion of population rootedness: their motivating example describes how a Boston-native is likely to have deeper family history in Boston than an LA-native would in LA. Their paper documents how rooted preferences for home have affected spatial propensities to migrate over time, including the propensity to return "home" after years spent elsewhere. Zabek (2019) builds on this idea in general equilibrium: strong ties to a place keep locals there in spite of better economic opportunity elsewhere. In turn, this lowers local wages, making the location even less attractive to outsiders who don't have ties to the place. Dynamic cities naturally have more population churn: local ties are naturally weaker there

[4] (Inflows + Outflows)/Stayers

and residents are more willing to pursue opportunity and amenities elsewhere.

In our valuation context, we remain agnostic on the specific mechanisms behind locational stickiness. We simply note that if low amenity places are indeed burdened with higher moving costs (and high amenity places are endowed with lower moving costs), a conventional stock-based model with homogeneous birthplace-derived moving costs may inaccurately characterize preferences for amenities. Our approach accounts for heterogeneous spatial ties by varying migration costs with a household's origin location. These additional modeling demands require a data environment that contains the origin and destination of household moves, as well as detailed demographic information on the household itself. We construct a database that meets these requirements and provides broad coverage of household residential movements between 344 metropolitan areas in the continental USA during the period 2012-2016[5].

The first piece of this database is an aggregated MSA-to-MSA migration flow matrix. This Census Bureau product provides an estimate of gross annual migration flows between MSAs based on 2012-2016 American Community Survey (ACS) responses. While the estimate is based on five years worth of data, it is generated from the ACS's annual survey question on where the household was located one year ago. We treat these aggregate flow estimates as a cross-sectional snapshot of migration in the US during the 2012-2016 period.[6] About 60% of the origin-destination pairs in our sample represent zero migration flows. Looking merely at this migration flow data, we can observe gravity-like aggregate behavior from migrants in Figure 3. Larger destinations (in terms of population) and shorter migration distances result in greater flows, thus motivating the estimation approach described in Section 4.1.

Next, we have collected a range of amenity data measured at the MSA-level. Our empirical application is focused on climate and air quality. Figure 4 maps out the spatial distribution of these key amenities. Our measures of climate amenities are straightforward: 30-year-averages (1980-2010) of summer temperature, winter temperature, and annual precipitation[7]. For air quality, we use average annual PM2.5 levels, a measure that encompasses the general, background air quality that people are likely to associate with a given city. Since these air quality and climate variables are generated from remote sensing data, we spatially weight our MSA-level measures using census tract populations[8]. Summary statistics and data sources for these variables and other key MSA-level measures are shown in Table 1.

We have also collected annual measures for a variety of other MSA-level amenities that have been

[5]There are actually 363 MSAs covered in our sample, but due to spatial boundaries in the microdata, we merged a subset of 35 MSAs into 16 super-MSAs. See below, and Appendix 3 for details.

[6]An alternative data product from the Internal Revenue Service (IRS) also measures population flows over space. They annually release county-to-county migration matrices based on counts of previous- and current-year tax filings. We rely on the Census measure for two reasons. First, the IRS data only counts tax-filing households. This may be problematic since a non-trivial percentage of US households do not file federal taxes. Second, the IRS data is highly censored: county-to-county flows of less than 10 households are not observable in the data.

[7]Summer temperature averages are over the months June, July and August. Winter temperature averages are over the months December, January, and February.

[8]Spatial resolution on the climate variables' grid is 4km; for the PM2.5 data it is roughly 1km.

shown to be important to quality-of-life. These include geographic, economic, transportation, and urban characteristics of a given MSA, and are described in Table 2. Insomuch as the previous literature has fretted over omitted variable bias in cross-sectional modeling of the determinants of location choice, we include this rich set of covariates to serve as controls in our main model specifications.

Finally, household-level data was obtained from public-use microdata (PUMS) created by the Census Bureau. PUMS are a 1%, nationally-representative sample of US households, taken annually. Microdata of this type has been used in many previous sorting papers; the data's principle advantage is its provision of broad information on households' demographics, employment, and location. In order to temporally match aggregate measures of migration flows across MSAs, we have collected samples of this microdata from the 2012-2016 period. Crucially, for the vast majority of MSAs, we matched surveyed households to their current MSA as well as their previous MSA (had they moved in the past year)[9]. Because we need to predict counterfactual incomes across MSAs in order to operationalize our empirical model, the microdata sample is cleaned by excluding households without an individual who earned more than \$5000 in wage income, households with only self-employed earners, and households with primary earners actively employed by the military. Summary statistics for the resulting sample of around 2.5 million households are shown in columns 1-2 of Table 3. To speed computation time for models relying on this microdata, all results in Section 6 are based on a 10% subsample, described in the middle columns of Table 3.

All together, our database includes complete amenity data, migration flows, and population microdata for 344 metropolitan areas in the US. These 344 MSAs account for over 97% of the 2012 urban population in the continental US; we deem this broadly representative of the US as a whole. MSAs included in our sample can be seen in Figure 4. In the analyses that follow, we assume migration between these MSAs occurs in a closed-system. Households can select to live only in these areas, and households originate only in these areas. When calculating migration shares from a given origin, the implication of this assumption is that the summation of flows across these 344 potential destinations serves as the denominator of the measure.

3 Conceptual framework

Our static MSA-level migration model builds from the canonical random utility approach commonly adopted in the context of location choice. Households make a one-time decision on where to locate, based on the costs and benefits of each potential destination. Given a choice set of J_k location options, let household i, originating in MSA k and moving to MSA j, receive utility

$$U_{ij}^k = U(Y_{ij}, h_{ij}, X_j, M_{ij}^k, C_i, \xi_j^k). \tag{1}$$

[9] See Appendix Table A2.1 for a list of omitted MSAs. Note that this matching exercise may result in small assignment errors for some MSAs, as geographic indicator boundaries in the microdata do not perfectly align with MSA boundaries. We discuss this in more detail in Appendix 3.

A household generates utility from its consumption of a tradable, numeraire good, Y_{ij}; a non-tradable local housing good h_{ij}; and a vector of MSA-level amenities, X_j. A household's well-being is net of any psychological or physical moving costs, M_{ij}^k, incurred from relocation. Preference heterogeneity arises from variation in observable household demographics, C_i. Finally, ξ_j^k denotes origin-destination characteristics that are unobserved by the econometrician.

Conditional on destination, j, a household maximizes utility by choosing consumption levels of the housing good and numeraire good subject to destination-varying budget constraints

$$W_{ij} = Y_{ij} + p_j(h_{ij}). \tag{2}$$

In Equation 2, W_{ij} denotes the household's location-specific income and $p_j(h_{ij})$ is the local expenditure level needed to purchase housing of a given quality h_{ij}. Income is the sum of wage earnings for all household members; we abstract away from non-wage income. The household determines its optimal location by selecting the destination with the highest location-conditional utility.

To solidify concepts, we envisage amenity levels (X_j) as common to all households who reside in MSA j. These average MSA-level characteristics - climate, background air quality, etc. - are our primary objects of interest for nonmarket valuation. Undoubtedly, access to some amenities varies spatially *within* MSAs, and should be correlated with intra-MSA land prices and wages (Cropper, 1981). In our framework, housing quality (h_{ij}) captures the role of localized amenities like schools or proximity to public transportation, in addition to accounting for physical characteristics and property size.

Adding structure, we study indirect utility functions of the general form

$$V_{ij}^k = f(W_{ij} - H_{ij}; \alpha) + v(X_j, M_{ij}^k, C_i, \xi_j^k; \beta) + \varepsilon_{ij}^k,\ j = 1, \ldots, J_k \tag{3}$$

where $v(\cdot)$ and $f(\cdot)$ reflect standard neoclassical microeconomic behavior. β is a vector of utility function parameters, α parameterizes the marginal utility of numeraire consumption, and ε_{ij}^k is a separable, unobserved, and idiosyncratic component of utility. We let $v(\cdot)$ be linear in parameters but allow for the interaction of its components, primarily to model preference heterogeneity based on observable household characteristics.

Our assumption of additive separability in the numeraire follows the approach of Plantinga et al (2013). Using a similar discrete choice model to study the role of housing prices on migration, that paper demonstrates that the separability assumption is a sufficient condition for specifying utility-maximizing housing expenditures as a function of household demographic characteristics. We leverage this result to estimate location-optimal housing expenditures, $H_{ij} \equiv p_j(h_{ij}^*)$, for each household. As we discuss in section 5, this permits households to optimally select different housing quality bundles across space, and does not depend on the Cobb-Douglas-based assumption that households spend a constant fraction of income on housing[10].

[10]The model in Sinha et al (2018) requires an assumption that households purchase the same housing bundle every-

Two noteworthy details follow from the setup. First, recall our primary focus is measuring a household's marginal willingness to pay for a given amenity, X^a. Taking the total differential of indirect utility, we have

$$dV_j^k = dX_j \frac{\partial v(\cdot)}{\partial X_j} + dM_{ij}^k \frac{\partial v(\cdot)}{\partial M_{ij}^k} + dY_{ij} \frac{\partial f(W_{ij} - H_{ij})}{\partial Y_{ij}}. \tag{4}$$

Setting all differentials to zero except for (i) our amenity of interest X_j^a and (ii) the numeraire good serving as our money metric, z_{ij},

$$0 = v_{X^a} dX_j^a + f_Y dY_{ij} \Rightarrow \frac{dY_{ij}}{dX_j^a} = -\frac{v_{X^a}(\cdot)}{f_Y}. \tag{5}$$

which is our simply-derived measure of marginal willingness to pay for a local amenity improvement.

Second, when ε_{ij}^k is distributed i.i.d. type I extreme value (EV1), the probability of household i settling in location j, conditional on originating in location k, can be conveniently expressed as

$$\Pr[V_{ij}^k \geq V_{il}^k, \forall l \neq j] \equiv \Pr_{ij}^k = \frac{\exp\Big(f(Y_{ij};\alpha) + v(X_j, MC_{ij}^k, \xi_j^k, C_i; \beta)\Big)}{\sum_{J_k} \exp\big(f(Y_{il};\alpha) + v(X_l, MC_{il}^k, \xi_l^k, C_i; \beta)\big)} \tag{6}$$

The mechanical, logit-derived relationship between observed choice probabilities in the data and utility as a function of origin and destination characteristics proves valuable for inferring the value of a location's amenities in a gravity-like fashion. We elaborate on this subject now while discussing our estimation approaches.

4 Using gravity to understand varying migration propensities

We now take the model to our data environment, viewing the study period as a single cross-section of location decisions. As described in Section 2, the data contains counts of average annual migration flows, where we observe population estimates of individuals relocating from an origin to destination location. We also work with a sample of household microdata that provides demographic information and residency locations over the past year. We refer to these as the aggregate and micro-level data, respectively, and again use $i = 1, \ldots, I$ to denote elements (i.e. households) of the micro-level data.

Denote by $j = 1, \ldots, J$ the universe of locations under analysis. Consider moves that originate at origin $k \in J$, and let $J_k \subseteq J$ denote the destination alternatives that are in the choice set for origin k households. Decompose indirect utility for a household i starting in location k and then migrating

where, while Bayer et al (2009) and most of the pursuant national sorting literature has relied on the Cobb-Douglas structure to fix a uniform share of household income spent on housing services at sample-calibrated values of around 0.2-0.25.

to destination j as

$$V_{ij}^k = \delta_j^k + \mu_{ij}^k, \; j = 1, \ldots, J_k \tag{7}$$

where δ_j^k is the deterministic average utility of moving to location j among households starting in place k, and μ_{ij}^k collects the household-specific components of utility that are both deterministic and random. In what follows, we leverage this delineation of indirect utility in two ways. First, we describe the model without household-level heterogeneity, and highlight what its gravity-like structure can tell us about a location's average attractiveness and migration propensity. Then we develop the full model for amenity valuation, incorporating microdata to study richer household-level preferences; our two-stage estimation method builds from the decomposition above to generate parameter estimates.

4.1 Stylized model with aggregate data

To develop an aggregate migration flow model, we assume μ_{ij}^k is i.i.d. type I extreme value. Thus, household deviations from origin-destination average utility are treated as random, meaning we study a representative, average household. Suppose a simple, linear-in-parameters average utility for households moving to j from k:

$$\delta_j^k = \alpha \bar{Y}_j + \beta X_j + \gamma M_j^k + \xi_j^k \tag{8}$$

where X_j is a vector of (observed) destination-specific amenity characteristics, M_j^k are (observed) migration cost factors with dyadic variation, and $\bar{Y}_j \equiv \bar{W}_j - \bar{H}_j$ is the average income of households in j, net of average housing expenditures.

Given the assumed extreme value assumption on μ_{ij}^k and the nature of δ_j^k, we can write the parameterized migration probability of a $k \to j$ move as:

$$\mathrm{Pr}_j^k = \frac{\exp\left(\alpha \bar{Y}_j + \beta X_j + \gamma M_j^k + \xi_j^k\right)}{\sum_{l \in J_k} \exp\left(\alpha \bar{Y}_l + \beta X_l + \gamma M_l^k + \xi_l^k\right))}. \tag{9}$$

As pointed out by Beine et al (2016), and earlier by Anas (1983), the random utility structure behind this choice probability yields a gravity-like equation when taken to the data. To see this, define S^k as the stock of households originating in origin k, and rearrange:

$$N_j^k \equiv \mathrm{Pr}_j^k \times S^k = \underbrace{\frac{\overbrace{(\exp\left(\alpha \bar{Y}_j + \beta X_j\right)}^{\phi_j} \overbrace{\exp\left(\gamma M_j^k + \xi_j^k\right)}^{\tau_j^k}}{\sum_{J_k} \exp\left(\alpha \bar{Y}_l + \beta X_l + \gamma M_l^k + \xi_j^k\right)}}_{\Omega_k} (S^k) = \tau_j^k \frac{\phi_j}{\Omega_k} S^k \tag{10}$$

The left-hand side variable, N_j^k is the aggregate gross flow of migrants from k to j, as observed in the data. Algebraically, this is equivalent to the predicted proportion of $k \to j$ movers multiplied by the population stock that began in k. On the equation's right hand side are the several structural components of gravity. The *push* factors pertain strictly to the origin location. Larger population flows originate from MSAs with high initial population stocks (S^k) or low levels of expected utility for prospective migrants (Ω_k), taking into account an origin's other potential destinations.[11]

τ_j^k captures the *friction* of movement from k to j. For $\gamma < 0$, τ_j^k must take a value less than or equal to 1, which implies smaller flows occur where the costs of migration between origin and destination are high. In this aggregate model, we specify distance-based migration costs in order to capture the inertial forces that keeps people from leaving their origin, and the psychological costs of moving longer distances from family and friends:

$$M_j^k = \sum_n \mathbf{1}\{\text{move distance} \in b(n)\} \tag{11}$$

This specification categorizes distances between origin and destination into the following seven bins, $b(n)$: 0km (staying in origin MSA), 0-250km, 250-500km, 500-1000km, 1000-2000km, 2000-3000km, 3000+km. We set 0km as our baseline bin, implying that the remaining bins' γ values should all be negative, and decease as the distance between j and k increases.

And finally, the model's *pull* factor (ϕ_j) describes the benefits of moving to destination j - the size of the observed migration flow should increase with the attractiveness of the destination. Here, a destination MSA's average net income and level of amenities both serve primarily as pull factors.[12]

4.2 Estimation and results

Our goal with the aggregate model is to present stylized evidence on the attractiveness and migration propensities of different MSAs. The former is crucial in a revealed preference sense: overall quality of life in our model is the combination of net income and localized amenities from which households derive utility. From this measure, we can break down trade-offs between income and amenities that allow us to calculate marginal willingness to pay for local characteristics. Migration propensities are also important: as we show below, population dynamics are heterogeneously fluid across space. If we do not control for this as a migration cost, we may infer a preference for amenities rather than an unrelated preference for place.

To recover these measures, we turn to econometric tools commonly used in the international trade

[11] As Beine et al (2016) point out, $\frac{\partial \Omega_k}{\partial \tau_l^k} > 0$ and $\frac{\partial \Omega_k}{\partial \phi_l} > 0$. In essence, this term captures how the characteristics of alternative potential destinations, l, affect the magnitude of an origin's population flows.

[12] One characteristic of an MSA that we treat as a pull factor is population. When $ln(\text{population}_j)$ enters as an element of X_j, we have the classic $\frac{P_1 P_2}{D}$ gravity structure described by Zipf (1946). The inclusion of population as a pull factor is a notable advantage of our framework. Equilibrium sorting models generally aim to predict population shares in each destination, rendering inappropriate the direct inclusion of population as a control. Since we predict origin-specific *migration shares*, we are able to control for this important regional characteristic.

and migration literatures. Our main estimation equation is written as:

$$N_j^k = \exp\left(\phi_j + \theta_k + \gamma M_j^k\right) \upsilon_j^k \tag{12}$$

The inclusion of a destination fixed effect, ϕ_j, indexes the attractiveness or quality of life in j. Ortega and Peri (2013) note that the inclusion of origin fixed effects, θ_k, captures multilateral resistances to migration that potentially exist in the origin dimension of Equation 10, $\frac{S^k}{\Omega_k}$. Put differently, a vector of origin fixed effects serves as an index of potential push factors and heterogeneity in the propensity to migrate across space. A well-behaved error term, υ_j^k, brings the model to data.

Since our dependent variable is always a non-negative integer, a count model is appropriate here. We estimate equation 12 by Poisson Pseudo Maximum Likelihood (PPML). This approach allows us to include origin-destination pairs with zero migration flows in our estimation sample, thus fixing $J_k = J, \forall k$ in the aggregate model. As demonstrated by Santos Silva and Tenreyro (2006) and Guimaraes et al (2003), this nonlinear estimator is appropriate in our context and remains consistent even when there is a high frequency of LHS zeros in the data or heteroskedasticity in the error term.

To accurately characterize heterogeneous migration propensities, we are most interested in getting at a measure of Ω_k. Since the set of estimated origin fixed effects resulting from equation 12 necessarily contains a population stock component, S^k, we derive our migration propensity index as the residuals of an additional linear regression:

$$\widehat{\theta_k} = \beta \ln(S^k) + \varepsilon_k. \tag{13}$$

Thus, we denote our migration propensity index as $\widehat{\varepsilon_k}$.

Tables 4 and 5 give a sense of the indices (ϕ_j, $\widehat{\varepsilon_k}$) that result from this empirical exercise. Table 4 displays the 25 least attractive destinations and 25 most retentive origins per the gravity framework. The destination MSAs populating this list are unsurprising - almost entirely smaller Rust Belt and Appalachian cities that have struggled economically over the past generation. The list of origin MSAs with low rates of population churn is more nuanced. Interspersed with declining and "sticky" Rust Belt cities are Floridian MSAs with high levels of less-mobile retiree populations and a large Sun Belt city (Houston) that seems to be retaining its residents exceptionally well. Despite these examples, the fact that many cities are jointly included on these lists provides suggestive evidence that low quality of life areas may have higher associated moving costs.

Table 5 tells the other side of the story. The most attractive MSAs, generally speaking, are large cities in the Sun Belt and Pacific/Mountain western states. Our index, derived fully from migration flow patterns, naturally mirrors the common growth narrative around these more affordable MSAs. Also in the top 25 are the amenity-rich and expensive coastal cities. In the right-hand columns, the 20 highest scoring MSAs on the migration propensity index tell a story that is less apparent on first glance. Most of these cities host military bases or universities, institutions that drive population churn organically (Watertown-Fort Drum, NY; Ames, IA; Lawrence, KS). Others are smaller Mountain/Western towns (Great Falls, MT; Missoula, MT; Medford, OR; Cheyenne, WY). And even controlling for population, our index finds that New York and San Diego both churn out migrants at a far higher rate than average.

Overall, these results tell a compelling and sensible story. In particular, they highlight heterogeneity in migration propensities across origins: a key result that motivates our empirical strategy in the next section. One additional detail to mention, however, is the potential to use this aggregate-flow-only framework to recover estimates of α and β in equation 10. Though the estimation results above lump these marginal values together in the quality-of-life index, a different approach could provide basic insights on average marginal valuations of individual amenities with very limited data requirements. To give a sense of this potential, we replace ϕ_j with its components $\alpha\bar{Y}_j + \beta X_j$ in equation 12, and re-estimate the model. These results are available in appendix Table A1.1. While these estimates are only suggestive, we find both parameter signs and magnitudes to be in the range of reason.

We proceed by estimating the full model with microdata in order to capture heterogeneous preferences and moving costs, address endogeneity concerns, and correct for potential Roy-like sorting, but note that the use of this aggregate-only framework for nonmarket valuation may be an interesting avenue in scenarios where microdata is unavailable and approximate estimates of MWTP would be policy relevant.

5 Empirical strategy for valuation: Incorporating microdata

Recall that our data environment also includes household microdata on a subset of migrants. We return to Equation 7, where we defined a household's indirect utility generally, and seek to make use of the additional information available in the microdata.

In order to model the household's decision directly, we again divide indirect utility into an origin-destination-pair average, δ_j^k, and household-specific component, μ_{ij}^k:

$$V_{ij}^k = \delta_j^k + \mu_{ij}^k$$

$$\delta_j^k = \beta X_j + \gamma M_j^k + \theta_k + \xi_j^k \tag{14}$$

$$\mu_{ij}^k = f(Y_{ij}) + \rho\eta_{ij} + \kappa M_{ij}^k C_i + \phi X_j C_i + \varepsilon_{ij}^k \tag{15}$$

There are several distinctions that result from our use of additional data. One is that net income and housing quality are now embedded in the household-specific component of utility. We specify $f(\cdot)$ as a piecewise linear spline with knots at the net income quintile cutoffs, $q_{(\cdot)}$, in our data's empirical distribution:

$$f(\cdot) = \begin{cases} \alpha_0 Y_{ij} & \text{if } Y_{ij} \leq q_{20} \\ \alpha_0 q_{20} + \alpha_1 (Y_{ij} - q_{20}) & \text{if } q_{20} \leq Y_{ij} \leq q_{40} \\ \vdots & \vdots \\ \alpha_0 q_{20} + \alpha_1 (q_{40} - q_{20}) + \alpha_2 (q_{60} - q_{40}) + \alpha_3 (q_{80} - q_{60}) + \alpha_4 (Y_{ij} - q_{80}) & \text{if } Y_{ij} \geq q_{80}. \end{cases}$$

This semi-parametric specification allows for well-established patterns of diminishing marginal utility from income and consumption (Layard et al, 2008), without imposing it directly on the data through the use of common log or quadratic functional forms.[13]

Households have distinct income and housing expenditures across potential destinations; we describe our counterfactual prediction procedures below. From these predictions, we also derive a household-specific measure of local housing quality selected, η_{ij}. Another distinction is that preferences for amenities are heterogeneous; deviations from an amenity's average marginal utility are captured in the model's household-specific component by interacting a potential destination's amenity levels with observable characteristics of households. Finally, we allow migration costs to depend on household characteristics:

$$M_{ij}^k = \gamma M_j^k + \kappa_1 M_{ij} + \kappa_2 C_i (\mathbf{1}\{\text{move distance} > 0\}) \tag{16}$$

In addition to the binned origin-to-destination-distance measure from our aggregate model (M_j^k), we also allow for varying migration costs to certain destinations based on a household head's birthplace. M_{ij} is a vector of three dummies taking on a value of zero if the potential destination is in the head of household's birth state, Census sub-region, or Census region. In the case of households "coming back home", this control reflects the reduced psychological costs of return migration. Our model also allows for demographic heterogeneity in migration costs through the interaction of a move/stay dummy with household characteristics. In particular, leaving one's current location may be more costly for households with children or multiple full-time earners.

5.1 Predicting counterfactual household variables

In the microdata, wages and housing expenditures are observable only in a household's chosen location. To estimate the model, counterfactual wages and expenditures are necessary for each potential destination. For this, we begin by estimating standard hedonic wage regressions using individual earners as the level of observation:

$$ln(wage_{ij}) = \alpha_j^w + \gamma_j^w C_i + \psi_{1,jk}\omega_{jk} + \psi_{2,jk}\omega_{jk}^2 + \varepsilon_{ij} \tag{17}$$

[13] Morey et al (2003) discuss the stepwise marginal utility functions that result from this specification and how to perform welfare analysis in light of the resulting discontinuities.

These regressions are run separately to obtain MSA-specific intercept and slope parameters[14]. Using the microdata, we keep part- and full-time workers in the estimation sample, but have dropped all observations where individuals earned wages of less than $5000 in the previous year. Fixed effects are included for industry and occupation. To correct for potential prediction bias resulting from nonrandom, Roy-type sorting, we follow Bayer et al (2009) in using Dahl's (2002) semi-parametric control-function correction. ω_{jk} denotes the worker-type-specific probability of regional migration. We create 16 distinct types by differentiating workers: they are binned by marital status, presence of children in the household, and which of four education levels they have obtained. We then calculate the empirical frequency of each type moving from one of nine census divisions to the others. Each worker in the estimation sample is assigned the resultant probability that matches their type, origin MSA, and destination MSA. The second-order polynomial of these worker-specific migration probabilities acts as a control function; the result is consistent estimation of the other hedonic parameters.

Estimation results are presented in appendix Table A1.2. Our results are largely in line with the long literature studying the hedonic decomposition of wages: experienced workers, more educated workers, males, and whites earn relatively higher wages. We use the resulting fitted values of these estimates as predictions of each individual's income in other locations. The assumption behind this, of course, is that individuals maintain similar work and hours, upon migrating. Then for each household, we sum individuals' annual wage earnings, yielding our counterfactual household income, $\widehat{W_{ij}}$.

The other counterfactual component of indirect utility is expenditures on housing. Because the numeraire is an additively separable component of our utility function, we build on Plantinga et al (2013) and write a household's optimal housing expenditures as

$$H^*_{ij} = p_j \left(h^*_{ij}(p_j, X_j, W_{ij}, C_i) \right) \equiv H_j(C_i, W_{ij}). \tag{18}$$

In each potential destination, the expenditure function H_j varies due to local implicit prices for housing and amenities. Since we observe households' optimal expenditures in their selected MSA, equation 18 indicates that we can empirically model them as hedonic functions of observable household characteristics, C_i, and the household budget, W_{ij}. To emphasize, these functions vary by MSA, accounting for regional differences in prices and amenities. As a result, in our specifications below, we let slope and intercept parameters differ by location.

As households could rent housing in one city and buy in another, we flexibly model their optimal expenditures by estimating MSA-specific ownership propensities, annual rental costs, and annual

[14]The list of individual characteristics included in these regressions can be found in appendix Table A1.2.

ownership costs[15]:

$$
\begin{aligned}
&ln(rent_{ij}) = \alpha_j^r + \gamma_j^r C_i + \iota_j^r W_{ij} + \varepsilon_{ij} \\
&ln(cost_{ij}) = \alpha_j^c + \gamma_j^c C_i + \iota_j^r W_{ij} + \varepsilon_{ij} \\
&\pi_{ij} \equiv Pr(own_{ij}) = \alpha_j^o + \gamma_j^o C_i + \iota_j^r W_{ij} + \varepsilon_{ij}.
\end{aligned}
\tag{19}
$$

Estimating hedonic regressions for each MSA separately, we use our microdata to find the parameter values in equation 19.[16] With these parameters, and relying on the counterfactual household income values we estimated in Equation 17, we predict, MSA-by-MSA, each household's rental costs, ownership costs, and probabilities of ownership as the resulting fitted values. Our ultimate counterfactual housing expenditure measure takes the predicted weighted average of costs

$$
\widehat{H_{ij}} = \widehat{\pi}_{ij}\widehat{cost}_{ij} + (1 - \widehat{\pi}_{ij})\widehat{rent}_{ij}. \tag{20}
$$

Our next step is to map these predicted optimal housing expenditures into a local measure of housing quality. In the structure described above, households choose their optimal amount of housing quality in MSA j, given the prices and amenities on offer there. As a result, households will buy more quality in some places, and less in others. To incorporate $\widehat{h_{ij}^*}$ into the indirect utility function, we assign each household the decile value (D_j) describing where its predicted housing expenditures fall in the MSA's true distribution of housing expenditures:

$$
\widehat{\eta}_{ij} = D_j(\widehat{H_{ij}}). \tag{21}
$$

The result is a housing quality index that runs from 0 to 9. For example, if $\widehat{H_{ij}}$ falls at the 83rd percentile of annual spending on housing in MSA j, $\widehat{\eta_{ij}}$ would be mapped to the value of 8. This reduced-form approach captures the spirit of Hamilton and Phaneuf's (2015) quality augmented local price indexes while maintaining lower data and computational requirements.[17]

With household incomes and housing expenditures predicted across each MSA, we obtain our variable of interest: $\widehat{Y_{ij}} = \widehat{W_{ij}} - \widehat{H_{ij}}$ is the counterfactual net income that serves as our measure of numeraire consumption.

[15] Annual costs are the sum of monthly mortgage or rent payments, plus associated utility bills, taxes, and insurance.

[16] The probability of ownership is specified as probit. Again, see appendix Table A1.2 for the list of household characteristics included in these regressions.

[17] To be clear, the pivotal assumption underlying this approach is that the distribution of housing quality is identical in each city. Per our indirect utility function, a housing quality measure of 8 in city j is implicitly equivalent to the measure of 8 in city k. While this does strike us as strong, we believe the flexibility afforded by our approach renders the assumption equally palatable to those made previously in the literature. Common sense suggests that the state of housing stocks and neighborhood quality varies across US metropolitan areas, but we are unaware of any research quantifying these distributional differences for all MSAs. There is research, however, showing people derive well-being from their *relative* local status in life; see Solnick and Hemenway (2005) for experimental results on housing consumption or Bottan and Perez-Truglia (2018) for evidence in a location-choice context. At a minimum, our housing quality measure captures this sentiment.

5.2 Maximum likelihood estimation

With all the relevant components of indirect utility now characterized, we proceed to describe our estimation of the model. Assuming ε_{ij}^k is distributed EV1, we return to the general logit structure of Equation 7 and adapt it to the specification laid out above. This is estimated by maximum likelihood, with the likelihood function given by

$$\mathcal{L}(\alpha,\rho,\kappa,\phi,\delta)=\prod_i\prod_{j=1}^{J_k}\left[\frac{\exp\left(f(\widehat{Y_{ij}})+\rho\widehat{\eta_{ij}}+\kappa M_j^k C_i+\phi X_j C_i+\delta_j^k\right)}{\sum_{J_k}\exp\left(f(\widehat{Y_{il}})+\rho\widehat{\eta_{il}}+\kappa M_l^k C_i+\phi X_l C_i+\delta_l^k\right)}\right]^{\chi_{ij}} \tag{22}$$

where χ_{ij} is a dummy taking on the value of one if household i migrates to j.

We obtain the parameters in Equation 22 using methods from industrial organization literature. The origin-destination-pair average utilities, δ_j^k, are estimated as alternative-specific constants (ASCs) in a first-stage logit model, then decomposed in a second stage linear regression (Equation 14) that recovers parameter estimates for β and γ. In our context, each origin serves as a "market"; thus, a flow from a given origin to destination is a *migration share*. Since the resulting parameter count is on the order of 10^4, to speed computation, we rely on a contraction mapping nested inside the first-stage maximum likelihood algorithm (Berry et al, 1995). Berry (1994) shows that the inclusion of a complete set of ASCs in a logit model results in perfect prediction of observed market shares. We use this moment condition to aid in our numerical parameter search. Denoting σ_j^k as a migration share observed in the aggregate data and $\widehat{\sigma_j^k}$ the maximum likelihood estimation's predicted migration share, each iteration (r) of the contraction proceeds as

$$(\delta_j^k)^{r+1}=(\delta_j^k)^r+ln(\underbrace{\sigma_j^k}_{\frac{N_j^k}{S^k}})-ln(\underbrace{\widehat{\sigma_j^k}}_{\frac{\sum_i Pr_{ij}^k}{I^k}})^r. \tag{23}$$

The key implication of this contraction approach is that δ_j^k is derived from the aggregate-level migration flow data, conditional on first-stage parameters which rely on variation coming from the microdata. A second point to note is our inability to estimate δ_j^k for origin-destination pairs with zero flows. When an empirical migration share falls to zero, the second term on the right side of Equation 23 becomes undefined. To deal with this shortcoming, we restrict choice sets by origin, imposing that households only consider migration to destinations where we see actual population flows occurring in the data. Therefore, the choice set J_k varies by origin.[18] A third and final point: since we can identify only J_k-1 of the ASCs in each vector δ^k, we elect to normalize $\delta_k^k=0,\forall k$. To account for this normalization in the second stage, we include origin fixed effects, θ_k, and thus rely on within-origin

[18] In their equilibrium framework for measuring total amenity expenditures, Bieri et al (2019) allow for consideration sets of a similar nature. Though their framework differs in key ways, they find little evidence that restricting the choice set in this way affects their results qualitatively. Future work - with more appropriate data - should more carefully study richer consideration patterns at the household level.

variation in all specifications.

5.3 Identification

In the demand estimation literature surrounding this classes of models, attention paid to identification issues typically focus on the second-stage regression. That is the case here as well: our model involves using a linear regression to decompose average utility into its observable and unobservable elements. From equation 14, we have

$$\begin{aligned}\delta_j^k &= \beta X_j + \gamma M_j^k + \theta_k + \xi_j^k \\ &= \beta X_j + \gamma M_j^k + \theta_k + \underbrace{\Delta_j + \nu_j^k}_{\xi_j^k},\ k = 1, \ldots, J_k,\end{aligned} \tag{24}$$

where each δ_j^k is recovered in the first stage maximum likelihood routine. This suggests estimating β and γ using a panel fixed effects model, where origins are the cross-sectional units and each origin contributes J_k observations. Thus, spatial variation in X_j from across the landscape, within origin variation in aggregate migration flows to destinations in J_k, and variation in the size and composition of J_k across origins are used to identify of the elements of β.

A challenge for consistent estimation is that the unobserved drivers of migration flows arise in part from unobserved amenities at the destinations. This is apparent when ξ_j^k is rewritten to reflect a destination-fixed component Δ_j and an idiosyncratic component, as in the second line of equation 24. Consistent estimation by least squares requires $corr(X_j, \Delta_j) = 0$, which is may not hold due to the tendency for different amenities to be correlated across the landscape. This suggests an instrument is needed for a potentially endogenous attribute like air quality.

We explore possible instruments for air quality by adapting strategies from the industrial organization literature, whereby attributes of competitors' products are used to construct an instrument for product price. In our case, we note that pollution concentrations are correlated across space due to geography and the location of emitters in the landscape. For example, if X_j and X_m denote air quality at locations j and m, it is likely that $corr(X_j, X_m) \neq 0$. This remains the case when there is a large distance between places j and m due to the strong effects of wind patterns and geography. At the same time, it is plausible that $corr(X_m, \Delta_j) = 0$ for large enough distances between the locations. Based on this logic we employ an instrumental variables strategy using

$$\tilde{X}_j = \sum_{m=1}^{J_{-k}} \mathbf{1}(\text{dist}_{jm} \in T) \left(\frac{1}{\text{dist}_{jm}} \right) X_m \tag{25}$$

as the instrument for X_j. $\mathbf{1}(\cdot)$ is an indicator function equal to 1 if the distance between j and m is in some threshold window, T. This is multiplied by the pollution level in m, then inversely weighted by the distance between j and m. All together, our instrument is an inverse distance-weighted sum of air quality. In constructing the instrument, we explore the robustness of results to different distance thresholds, T, and to summing over the full set of locations J versus the subset J_{-k}, defined as the set of destinations not in the choice set for origin k. Summing over the subset of MSAs not in an origin's choice set is potentially compelling here: it provides instrument variation in the origin-destination pair dimension and relies on air quality measures in places excluded from household consideration by our model's construction.

Finally, our preferred instrument also incorporates wind patterns, a substantial component of localized pollution that is plausibly exogenous. Taking the logic and data from Deryugina et al (2019), we leverage the North American Regional Reanalysis (NARR) daily satellite wind direction data to calculate the percentage of days from 2012-2016 that wind blows from a neighboring MSA, m, into the destination MSA, j. More formally, we sum the number of days that wind in MSA j came from a directional angle in the 45° window around the compass bearing between m and j, and then divide by the count of days over the 2012-2016 period.[19] This measure, w_{jm}, is then interacted with the instrument measure above, generating the new sum:

$$\tilde{X}_j = \sum_{m=1}^{J_{-k}} \mathbf{1}(\text{dist}_{jm} \in T) w_{jm} \left(\frac{1}{\text{dist}_{jm}} \right) X_m. \tag{26}$$

This preferred instrument captures the decaying nature of air pollution over distance and increasing effect of wind direction, summing these weighted values over MSAs that are assumed independent from the household's location choice at hand.

We illustrate two versions of these instruments on a map in Figure 5. Panel A displays a case where all MSAs located at a distance within 100 to 1000km of the destination (Madison, WI) contribute to the instrument. Winds from the south and west dominate in Madison, so pollution from neighboring MSAs in that direction contribute relatively more to the instrument. Panel B displays a case where only MSAs outside the choice set of the origin (Tucson, AZ) contribute to the instrument.

These instruments' validity hinge on the assumption that $corr(X_m, \Delta_j) = 0$, which we believe is plausible in our migration flow context. Note in particular that ξ_j^k in equation 24 arises from origin-specific migration shares, rather than the overall share of the population that resides in location j in spatial equilibrium. This is an important distinction between our approach based on flows, and models that use the stock of residents at a location to estimate preferences. In our case, the main endogeneity problem is omitted correlated amenities, which we address with a rich set of controls and our instrument. In applications using aggregate population shares, however, the main endogeneity problem is simultaneous determination: amenities X_j and ξ_j are joint endogenous outcomes in the spatial equilibrium, making identification more challenging. Thus, the distinct sources of variation used in flow versus stock models should condition how we evaluate the validity of identification assumptions in each context.

[19] Since the satellite data is on $2.5° \times 2.5°$ grid, our daily measure of an MSA's wind direction is the spatial average of relevant grid cells, weighted over the MSA's entire land area.

6 Results

We start by discussing our full model's baseline results, which focus on mean MWTP estimates for our amenities of interest. The key parameter estimates for this model are in Table 6. The first-stage, household level parameters - estimated by maximum likelihood and shown in Panel A - are in accordance with our priors. The (piecewise) marginal utility of income is shown to be diminishing, moving costs specific to the household are sizable and of the correct sign, and the marginal utility obtained from housing quality is positive.

Panel B contains the parameter estimates for the second-stage, linear regression. Recall that we are regressing the average origin-destination utility level on a set of destination characteristics, an origin fixed effect, and a vector of distance bins that proxy for distance-related moving costs. The four sets of results here are from separate models; column (1) is a standard least squares estimator, while columns (2)-(4) use different versions of our instrumental variable to address endogeneity concerns about the air quality parameter. Because we are interested in a nationally representative estimate of mean MWTP, we use generalized least squares in all specifications, weighting observations by their origin's population divided by the size of the origin's choice set.

The economic interpretation of our key parameters holds across specification, though the magnitudes vary slightly with the introduction of the instrument. As we expected, households prefer drier climates, warmer winter temperatures, cooler summer temperatures, and cleaner air. As a point of comparison, the model in column (1) finds that a household earning close to the median national income has an annual MWTP of $584 for a one unit reduction in PM2.5. Column (2) instruments for PM2.5 using a distance- and wind-weighted sum of pollution from **all** neighboring MSAs that fall between 100 and 1000 km from the destination. Our comparison household's implied MWTP for cleaner air more than doubles to $1,217. Column (3) uses an instrument that does not weight by wind direction, and sums distance-weighted pollution from neighboring MSAs that *are not* in the origin's choice set. The magnitude of MWTP for cleaner air grows further, to just over $1,430.

Finally, column (4) uses our preferred instrument, essentially combining the approaches in columns (2) and (3). We sum distance- and wind-weighted pollution from neighboring MSAs that are not in the origin's choice set. When including the exogenous influence of wind direction, the magnitude of the parameter on PM2.5 is dampened significantly relative to column (3). Our comparison household has a MWTP of $818 for cleaner air in this preferred model. This household also has a MWTP of $1,647 for a one degree (Celsius) warmer winter temperature, $846 for a one degree cooler summer temperature, and approximately $105 for 1 cm less annual precipitation.

Stepping back for a broader view, Figure 6 traces out the average MWTP curve for each of our four environmental amenities of interest. These stepwise curves illustrate how MWTP for these amenities increases with household income levels.

6.1 Benchmarking against stock-based models

Next, we contrast our model's results against those from a conventional national sorting model. In sorting models powered by the distribution of population stocks over space, first stage estimation is nearly identical to our framework, but ASCs are included only for destinations. In other words, there are 344 ASCs in the conventional model versus over 40,000 in our migration flows model. Origin does not play an essential role in stock-based settings; the model's second stage simply regresses each destination's average utility on its set of amenities.

Results in Table 7 underscore some of the advantages of our approach. To ensure full comparability, in all three specifications shown, we use an identical IV (see column 2 of Table 6) and the same sample of data. Column (1) shares parameter estimates for a standard stock-based model. As the first-stage parameters look broadly similar to those in our flow model, our ultimate interest is primarily in the second stage estimates. Here, the parameters for climate amenities are correctly signed and of sensible magnitude. However, we find a perverse sign on PM2.5, *despite* use of an IV. This is a fairly regular phenomenon in this literature, and indeed motivates Bayer et al's (2009) use of temporal first differences to absorb MSAs' time-invariant unobservable characteristics. Additionaly, due to the comparative paucity of observations ($N = 344$) in the second stage of the conventional model, parameter estimates are imprecise.

We next turn to an adaptation of this stock-based model in column (2). The two most apparent differences between conventional stock models and our flow model are the dimensionality of ASCs and the inclusion of distance-based migration costs. To isolate the role of these differences, we run a stock-based model that includes corresponding origin-to-destination distance bins in the first stage. The resulting second stage estimates from this specification are noisy: the sign on air quality flips, but its magnitude is implausibly large and the estimate is imprecise. Furthermore, the sign on the summer temperature parameter flips, and its magnitude also grows substantially.

Column (3) re-displays flow-based results from Table 6 that rely on an instrument identical to the one used in columns (1) and (2). Structurally, this model is identical to column (2) except it uses ASCs derived from flows instead of stocks and therefore includes origin fixed effects in the second stage. This flow model is the most directly comparable to the stock models we've presented here. Looking across columns, our flow approach appears to deliver the strongest results. Our take-away from this set of estimates is that our flow model's key innovation is the inclusion of both origin and destination in our ASCs. The dimensionality and richer spatial variable available in our approach's second stage produces estimates that are plainly preferable to the conventional sorting model. Of course, as mentioned, we have avoided inclusion of a temporal dimension here - a tactic that would surely improve the quality of estimates from the stock-based models. Nonetheless, we note that our model manages to consistently sign the parameter on air quality correctly without this temporal dimension, and even without use of an IV.

6.2 Robustness

We also consider our preferred baseline model's robustness to specification and sample selection. We first re-examine our utility function's treatment of net income; our model relies on a separable piecewise linear spline. Using this semi-parametric technique in Table 6, we found point estimates that met our priors - marginal utility from income is diminishing. Nonetheless, the convention in the literature has been to allow income to enter the utility function linearly or logarithmically. We estimate models using these more restrictive assumptions and show the results in Table 8.

Column (1) shows point estimates when income enters the utility function linearly; as is well known, this assumption fixes the marginal utility of income as constant. In monetary terms, we find the resulting mean national MWTP for a one unit reduction in PM2.5 to be on the order of $1,800. This is more than twice as large as the value implied by our preferred model for a household earning the median income. Indeed, this value is even larger than the implied air quality MWTP ($1,750) for households in the top income quintile under our preferred income specification.

Similarly, we find larger MWTP estimates when income enters logarithmically. In this specification, marginal utility is restricted to fall proportionally with the household's income level. Parameter estimates are shown in column (2). For a household earning $60,000 income net of housing, the implied MWTP for a one unit reduction in PM2.5 is around $2,950. In imposing the logarithmic functional form to capture diminishing marginal utility in the standard way, we've forced the marginal utility of income to diminish faster than shown by our piecewise linear estimates. Conditional on the rest of our model's structure, this logarithmic assumption results in MWTP estimates that we find implausibly large for much of the income distribution.

As a final point before moving on to sample robustness, we emphasize that in most applications of discrete choice sorting models, measures of MWTP are a ratio of only two parameters. The functional form chosen for the marginal utility of income defines one half of this equation; ensuring the credibility of its estimate is of utmost import if we are to believe the values of MWTP implied by our model. We feel that our semi-parametric approach to estimating the marginal utility of income is a novel step forward, but encourage further exploration of this matter in future work.

Moving along, Column (3) of Table 8 shares parameter estimates when our model is estimated on a movers-only subsample of the national population. More specifically, the sample includes only households who had moved from their previous residence to a new one in the past 12 months.[20] Previous work has suggested that these households might be closer to "in equilibrium" than households who stay in place, and that this can contribute to the gap between MWTP estimates from hedonic and sorting models. Indeed, Wong (2018) intuitively demonstrates under strong but tractable conditions that inframarginal households have indifference curves that are unlikely to fall tangent to the hedonic price function.

This sample of households differs substantially from our national sample (see Table 3 for summary

[20] We also adjust the aggregate MSA-to-MSA migration flow matrices to include only population counts who moved in the past year.

statistics), but the parameter estimates imply mean MWTP values roughly in line with those from the complete national sample. A household at the median net income level has a MWTP for lower PM2.5 of $1,092. Interestingly, the estimated marginal utility of income for recent-movers earning in the top income quintiles is substatially larger than that estimated for the population as a whole; the resultant MWTP curves are much flatter for recent movers than those illustrated for the entire population in Figure 6. As discussed above, this accords with economic intuition - households who move are perhaps more likely to relocate for a wage premium or housing discount than the population's average household.

6.3 Heterogeneity in preferences

Next, we use variation in observable characteristics to study heterogeneity in household MWTP for environmental amenities. As in previous sorting work, we begin by interacting demographic characteristics with amenity levels at the destination; from this first-stage interaction, we can see how preferences vary across subgroups of the population. Here, we study how tastes vary for households with older (> 55 years), younger (< 25 years), or more educated (college grad) heads, as well as those with children present.

Parameter estimates are shared in Table 9; note that reported values in this table are from a single estimated model. Panel A contains the heterogeneity-related parameters, while Panels B and C hold the the homogeneous parameters familiar from previous specifications. Several findings common to the literature emerge from these results: college grads are substantially more sensitive to environmental amenities than the population at whole, older populations sort heavily on temperature amenities, and there seems to be relatively limited heterogeneity in distaste for PM2.5. As there are many dimensions of heterogeneity occurring here simultaneously, we focus on a single set of subgroups in order to illustrate the richer MWTP patterns. In Figure 7, we trace out MWTP curves separately for households with older, prime-aged, and younger heads. As expected, some notable variation in tastes is masked by simply looking at mean MWTP estimates. The average distaste for annual precipitation level is driven almost entirely by younger households, while a similar story applies for older households' aversion to warmer summer temperatures. Note that these MWTP estimates rely on homogeneous marginal utility of income across subgroups; an interesting but computationally-costly potential avenue for future work would be the accommodation of demographic-driven heterogeneity in this dimension as well.[21]

Next, we study how preferences may vary *by origin*. While others in the sorting literature have studied preference heterogeneity conditional on destination via random coefficient models, the structure of our model lends itself to the study of how tastes vary by origin. To illustrate this, we use the ASCs recovered from our preferred baseline model in Table 6 and estimate a second-stage regression where destination amenity levels are interacted with dummy variables indicating the quintile of the origin's amenity level. For example, a very cold city - say Fargo, ND - would fall into the lowest

[21] In an unpublished working paper, Lee (2017) emphasizes this very point.

quintile (Q1) for average winter temperature. Through the use of these interaction terms, we can study how preferences for climate or air quality differ conditional on a household's origin baseline amenity level.

Results from this second stage regression are shown in Table 10. Some findings suggest a degree of previous sorting on environmental preferences: households in drier origins have the strongest average distaste for precipitation, and households in the coldest origin cities strongly prefer cooler summer temperature. On the other hand, we surprisingly find that the strongest preferences for warmer winter temperatures comes from households in colder origin cities. One explanation for this might be that moving costs from the these colder origins in the upper Midwest and East coast are larger than average. Despite stronger preferences for warmer winter temperatures, many households from these origins remain close to home. And lastly, we find that households with the strongest distaste for PM2.5 are from origins falling in the middle of PM2.5 distribution. Notably, those from origins with the highest levels of particulate pollution appear not to value cleaner air at all.

Finally, we highlight an additional dimension of preference heterogeneity offered by our framework that could be of interest in other applications. It would straightforward but computationally expensive to incorporate household-by-origin preference heterogeneity in the first stage of our model or estimate separate ASCs by demographic group. Despite these computation costs, we can imagine the interplay of demographic characteristics and place as particularly interesting in the context of the environmental justice literature; perhaps this flavor of sorting framework could shed new light on nuisance-driven residential mobility (Depro et al, 2015).

7 Conclusion

Beginning with Bayer et al (2009) researchers have recognized that moving costs are important for measuring the marginal willingness to pay for regionally varying environmental amenities using location choices. These moving costs drive a wedge between amenity values and gradients estimated using wage and home price hedonic regressions. In the national sorting model literature these moving costs are proxied using a household head's birth location. Recent literature in urban and labor economics, however, has documented that there is place-based heterogeneity in moving costs. Some places are "stickier" while other locations display a lot of "churn". If low quality of life locations are also places that are costlier to leave – an empirical regularity that we document – we may incorrectly conclude from the spatial distribution of population stocks that local amenities are not important to households. Our main contribution in this paper has been to develop and estimate a generalization of the familiar national-level sorting model that accommodates heterogeneity in migration costs across different origins by exploiting information on migration flows.

We find that estimates of marginal willingness to pay for air quality and climate amenities from our migration flow model are more plausible and better identified than corresponding estimates from a conventional cross-sectional sorting model. Observation of both origin and destination in our aggregate and household-level migration data allows us to: (a) include origin fixed effects in our model; (b) treat each origin as a separate market in our discrete choice model; and (c) , and identify average marginal utilities using within origin variation in average preferences for destinations. Relative to using population stocks, these innovations provide more precision – our second stage regression is an unbalanced panel in origin MSAs rather than a single cross section of MSAs – and opportunities for identification based on spatial differences. Second stage estimates of marginal utilities for air quality and climate amenities from our migration flow model are intuitive and qualitatively similar in sign and significance across OLS and IV estimators; in contrast, second stage IV estimates from the conventional population stock model are imprecise and in some cases perversely signed. This provides at least suggestive evidence that it is possible to consistently estimate preferences using a standard IO-literature instrument and without temporal first differences when migration flow data are available.

Specifically, our IV estimator is motivated by the older empirical IO literature that uses attributes of competing products as instruments for endogenous attributes, and recent literature in environmental economics that uses wind direction as an exogenous source of variation in pollution. Since we calibrate average utilities for destinations using migration flows from specific origins, rather than equilibrium population stocks, endogeneity problems for attributes like air pollution are more likely to arise from correlated omitted attributes and measurement error, rather than simultaneous determination in equilibrium. As a result, the exclusion restrictions needed for consistency of our IV estimator are more credible in our migration flow model than they are for a population stock model, and our estimates from the two models show this in practice.

In addition to our main innovation of using migration flow data, we also investigate an alternative functional form for how net income enters utility, which provides a flexible representation of the marginal utility of income across income levels. We find using our piece-wise linear representation that the marginal utility of income falls off at a slower rate than is implied by the commonly used log transformation. This has important ramifications for marginal willingness to pay estimates, and our results suggest this is an important topic for further research.

We close by noting that our migration flow model could be useful for other applications in environmental economics. Our examination of heterogeneity in this application has been largely illustrative, but our ability to differentiate marginal willingness to pay across income groups, household types, and geography could be useful for understanding the distributional consequences of environmental policy. Estimating a generalized version of this model that differentiates moving costs based on household types could be useful for environmental justice type questions. We leave these ideas for further research.

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Figures and Tables

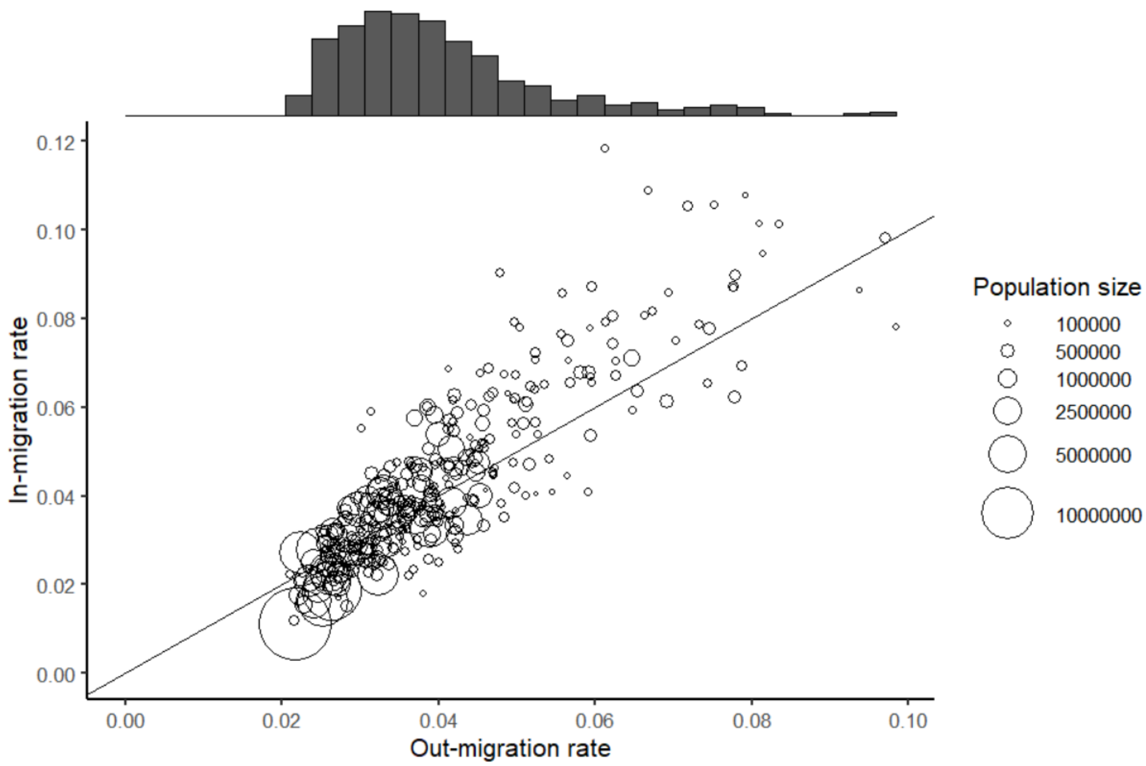


Figure 1: Net migration flows provide a fuller picture of migration patterns than population stocks. Each point represents a MSA included in our study sample (N=344). Points' size denotes the MSA's 2016 population size. Histogram of MSA out-migration rates, a measure of interest to us, shown above scatterplot; this illustrates rich heterogeneity across MSAs. Population size underlies this heterogeneity. Due to scale, percentage in- and outflows are smaller in large cities. 45-degree line maps equal replacement; deviation from this line denotes population growth or decline in an MSA. Data: US Census Bureau, 2012-2016.

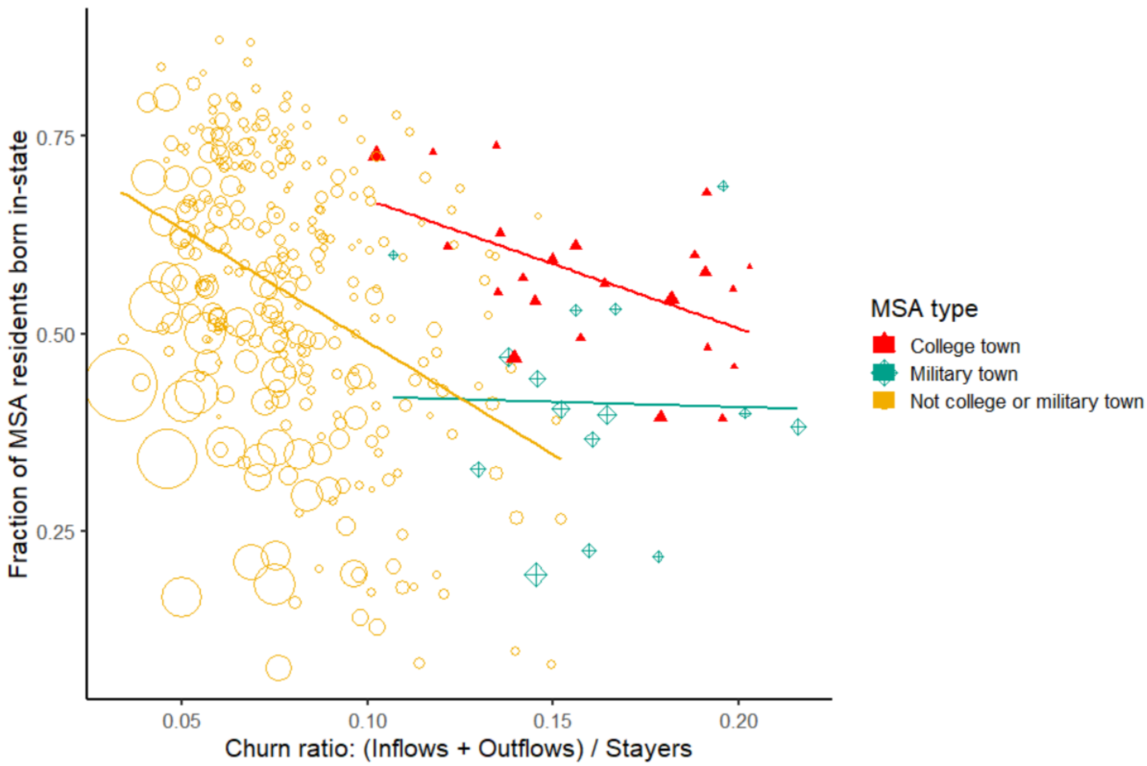


Figure 2: Sticky MSAs are those with less overall churn. Each point represents a MSA included in our study sample (N=344). Churn here is defined as total in- and out-migration counts divided by the count of people staying in place. The correlation between churn and rates of birth-state residency is partially mechanical: more churn may bring in more out-of-birth-state individuals. Nonetheless, research designs relying on distance from birthplace as a proxy for household moving costs miss important heterogeneity in leaving a *certain* place. Note: "College towns" and "military towns" are differentiated here as they inherently create churn. The former are defined as MSAs with $> 15\%$ of residents enrolled in college (data: Census Bureau, 2012-2016). The latter are defined as MSAs where $> 8\%$ of the labor force is employed by the military (data: Bureau of Economic Analysis, 2016).

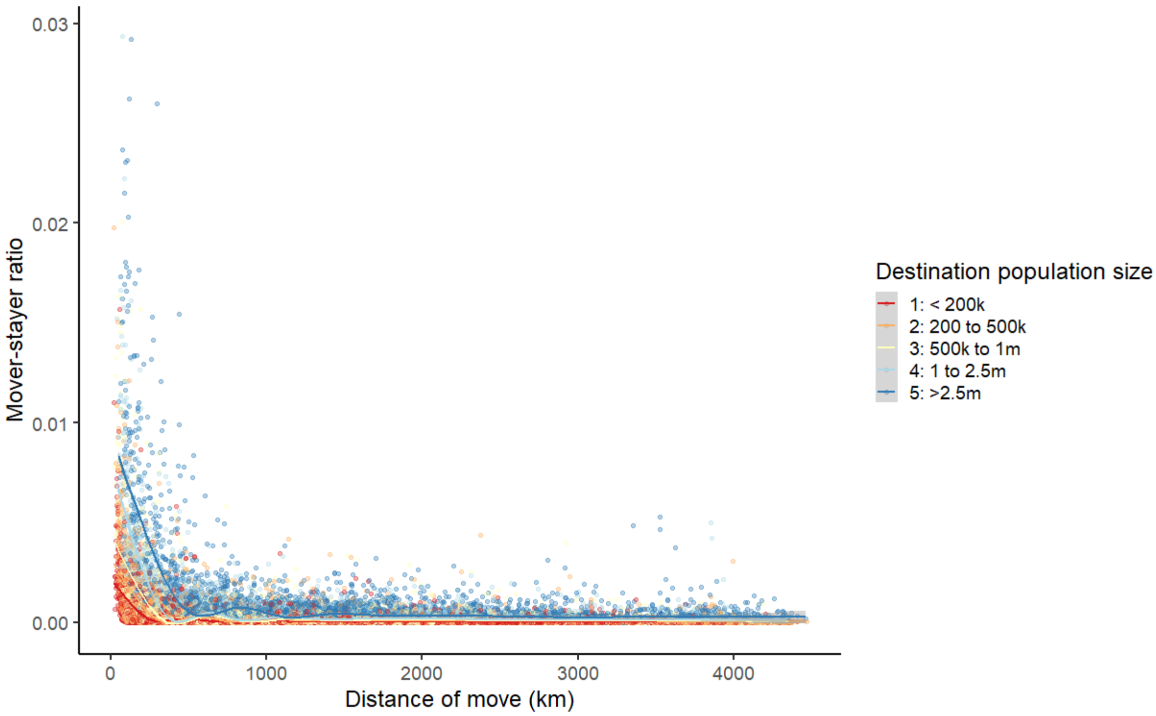
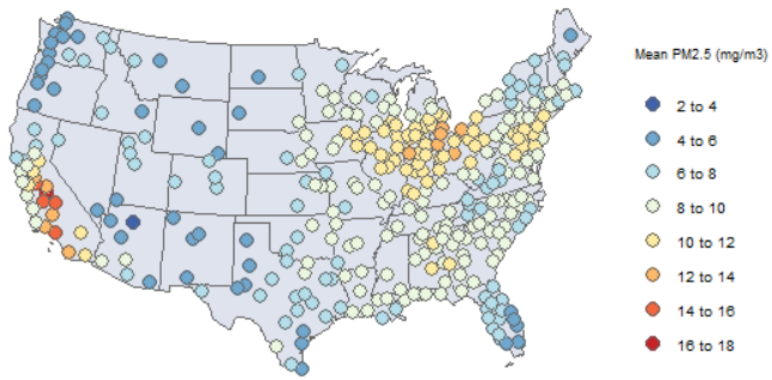
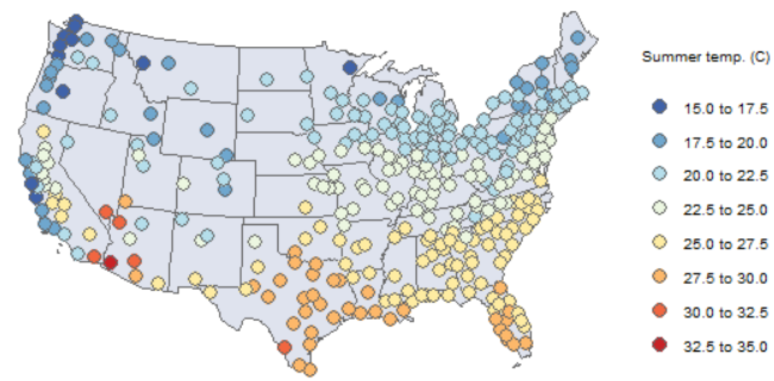


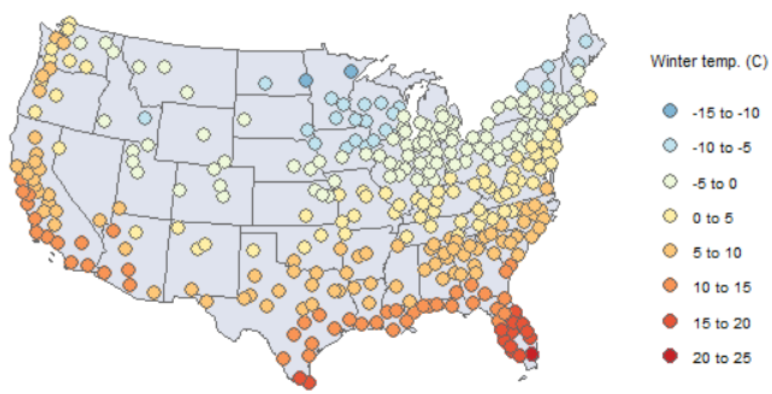
Figure 3: Gravity illustrated. Each point denotes an origin-destination-pair observation (N=118,336). Mover-stayer ratio is the population moving to an observation's destination divided/normalized by the population staying in the observation's origin. Two takeaways are evident and familiar: distance and destination size are key determinants of migration. Plotted curves are cubic splines over distance for destinations of different population sizes. Data: US Census Bureau, 2012-2016.



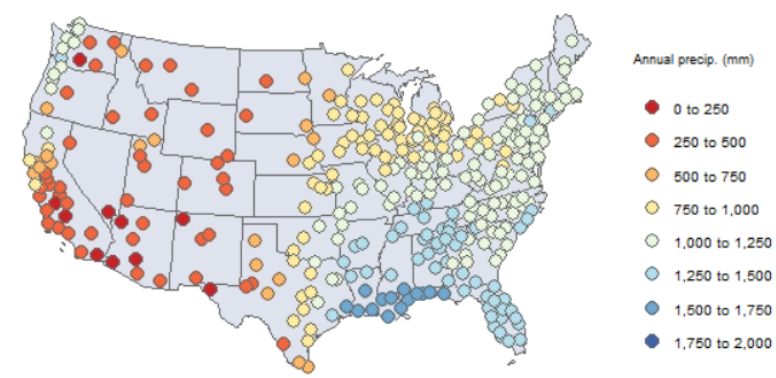
(a) Between-MSA variation in average PM2.5 ($\mu g/m^3$)



(b) Between-MSA variation in average summer temperature (Celsius)

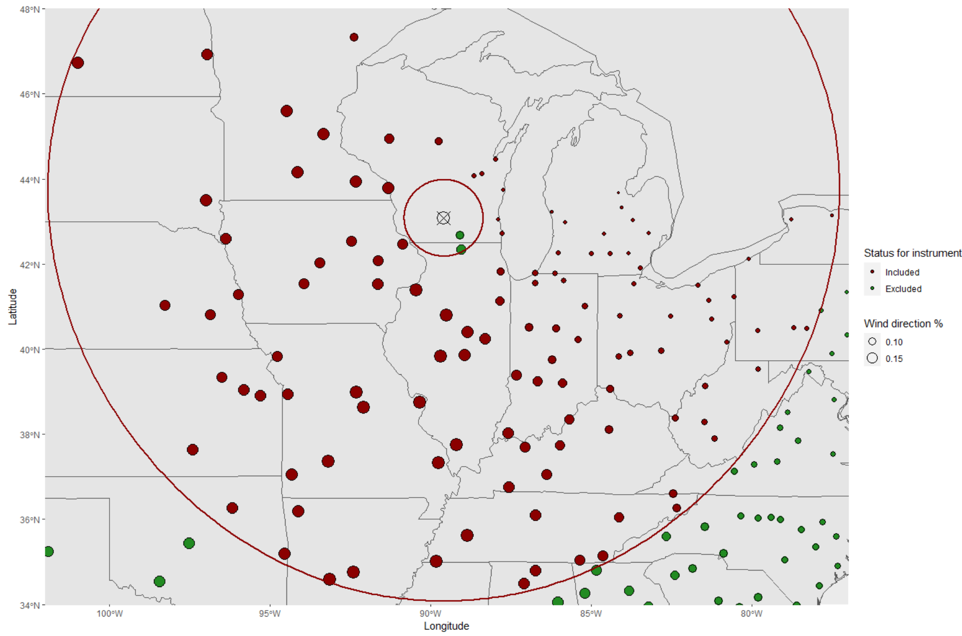


(c) Between-MSA variation in average winter temperature (Celsius)

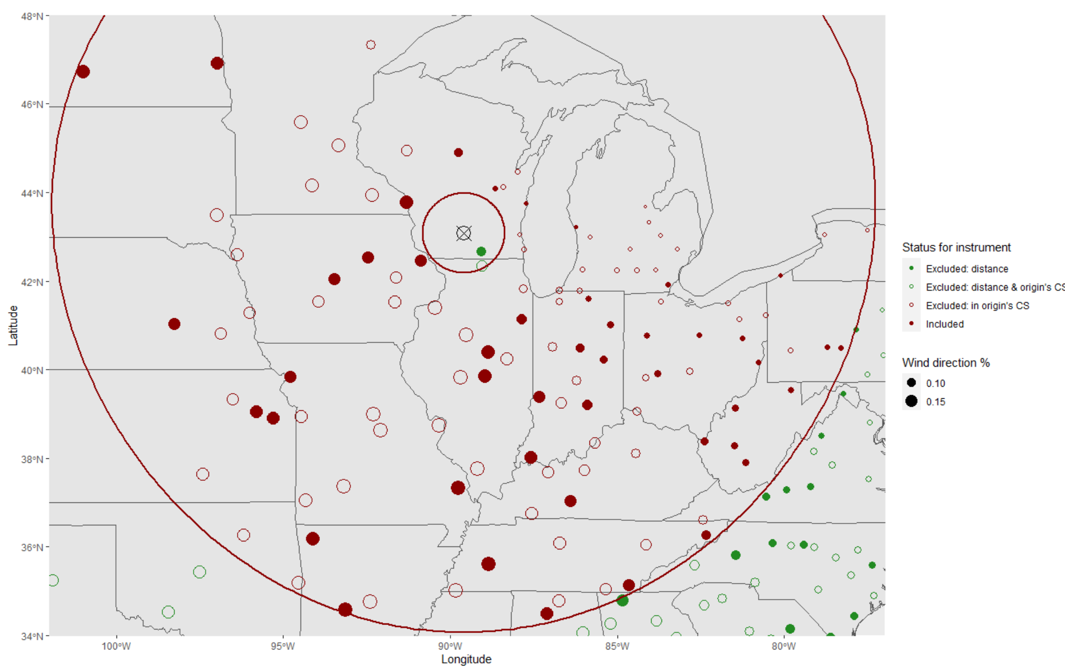


(d) Between-MSA variation in annual precipitation

Figure 4: Visualizing levels across space for environmental amenities of interest.



(a) IV: distance- and wind-weighted sum of incoming pollution from neighboring MSAs, not within 100km of the destination.



(b) IV: distance- and wind-weighted sum of incoming air pollution from neighboring MSAs that are not in the origin's choice set and not within 100km of the destination.

Figure 5: Visualization of logic behind our instrumental variable strategy. In both panels, the destination city is Madison, WI; the origin city (out of frame) is Tucson, AZ. Our instrument sums distance-weighted (and in some cases, wind-weighted) PM2.5 levels from cities that neighbor Madison. Across panels, MSAs less than 100km from Madison are excluded, as are those greater than 1000km away. See Table 6 for comparison of estimation results using different flavors of this IV.

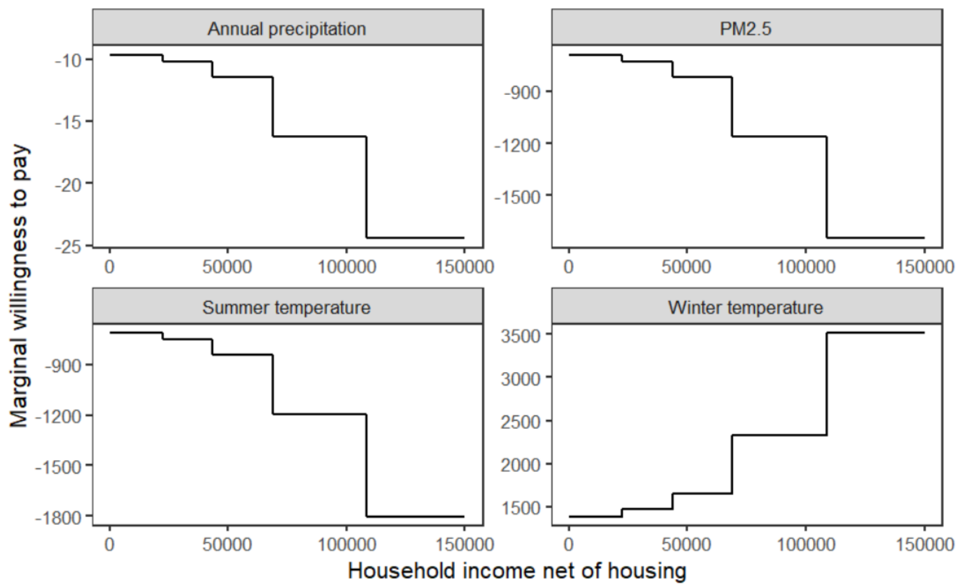


Figure 6: Tracing out the average marginal willingness to pay curve, by net income level and amenity. Parameters estimates taken from Table 6, column 4.

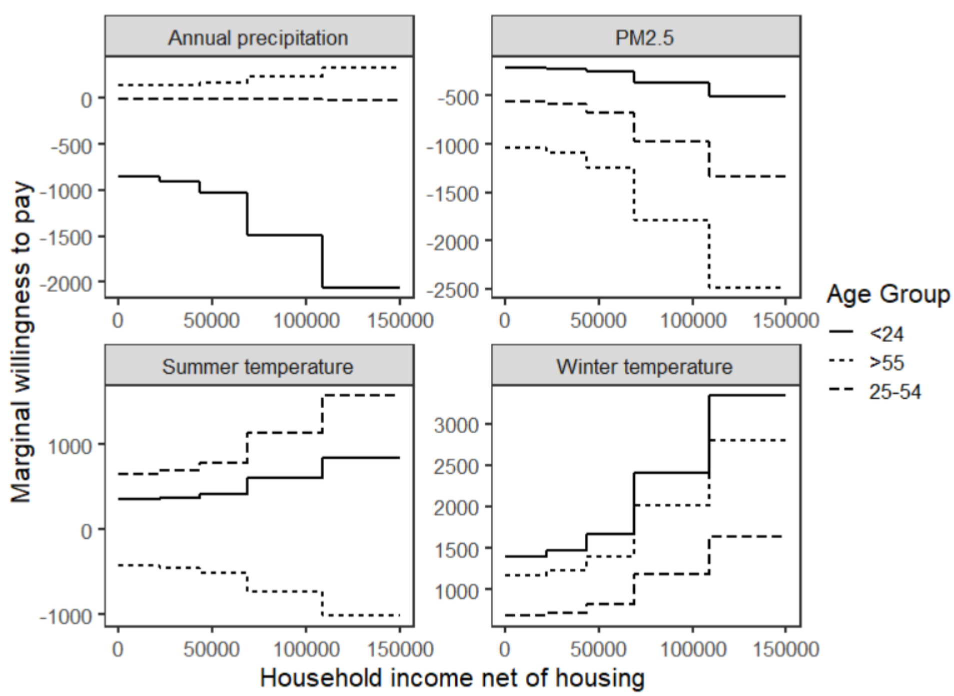


Figure 7: Tracing out marginal willingness to pay when preferences vary by observable demographics. Here, MWTP varies with the age of household head. Parameter estimates taken from Table 8.

	Mean	St.Dev	10th percen.	90th percen.	Source
Mean PM2.5 ($\mu g/m^3$)	8.649	2.088	5.691	11.230	Van Donkelaar et al (2012-16)
Annual Precipitation (mm)	974.4	353.2	390.5	1360.1	PRISM (1980-2010)
Mean Winter Temp ($^\circ$C)	3.311	6.421	-4.083	11.59	PRISM (1980-2010)
Mean Summer Temp ($^\circ$C)	23.52	3.251	19.69	27.57	PRISM (1980-2010)
Mean household income ($)	69879	12408	57862	84020	Census Bureau (2012-16)
Median household rent ($)	11037	2735	8344	14664	Census Bureau (2012-16)
Population	763002	1680456	114482	1842424	Census Bureau (2012-16)
MSA count:	344				

Table 1: Summary statistics for MSA-level variables of primary interest. All annual average measures generated from remote sensing sources (climate, PM2.5) are weighted by population at the census tract level.

	Variable	Source
Geographic		
	Average Elevation	Authors' calculations
	Ruggedness (TRI)	Riley et al (1999)
	Coastal (dummy)	Authors' calculations
	Total Land Area (km^2)	IPUMS-NHGIS (2011)
	% Water Area	IPUMS-NHGIS (2011)
	% Developed Area	IPUMS-NHGIS (2011)
	% Urban Open Space	IPUMS-NHGIS (2011)
	% Forest Cover	IPUMS-NHGIS (2011)
Economic		
	Local Gov't Spending Index	Stansel (2013)
	Local Tax Index	Stansel (2013)
	Local Labor Index	Stansel (2013)
	Local unemployment rate	Census Bureau (2012-2016)
	% employed in the arts	Census Bureau (2012-2016)
	% employed in manufacturing	Census Bureau (2012-2016)
Transport		
	Average Commute Time	Census Bureau (2012-16)
	Public Transport Usage (% of pop)	Census Bureau (2012-16)
Urban Amenities		
	Libraries/km^2	IMLS (2016)
	Museums/km^2	IMLS (2016)
	Recreation Facilites/km^2	USDA (2015)
	Farmers' Markets/km^2	USDA (2015)
	Full-service Restaurants/km^2	USDA (2015)
	Fast-food Restaurants/km^2	USDA (2015)
	Malls & Supercenters/km^2	USDA (2015)
	Grocery Stores/km^2	USDA (2015)
Urban Disamenities		
	Annual Violent Crimes (per 100k)	FBI (2012-16)
	Annual Property Crimes (per 100k)	FBI (2012-16)
	Brownfields/km^2	EPA (2012)
	Superfund/km^2	EPA (2012)
	Annual Extreme Weather Events	NOAA (1996-2011)

Table 2: List of additional urban characteristics included as MSA-level amenities.

	Full sample		Estimation sample		Movers-only sample	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Net HH income	74794	(81894)	75104	(82335)	60978	(70984)
Multiple earners in HH	0.389	(0.488)	0.389	(0.487)	0.350	(0.477)
Child in HH	0.479	(0.5)	0.479	(0.5)	0.370	(0.483)
HH head: Age	46.596	(12.428)	46.590	(12.429)	37.848	(12.23)
HH head: Female	0.438	(0.496)	0.439	(0.496)	0.459	(0.498)
HH head: Married	0.573	(0.495)	0.574	(0.495)	0.389	(0.488)
HH head: College grad	0.459	(0.498)	0.460	(0.498)	0.492	(0.5)
HH head: Black	0.088	(0.283)	0.087	(0.282)	0.096	(0.295)
HH head: Other non-white	0.121	(0.326)	0.120	(0.325)	0.144	(0.351)
HH head: Hispanic	0.132	(0.338)	0.131	(0.338)	0.143	(0.351)
HH head: Reside in birth state	0.471	(0.499)	0.472	(0.499)	0.428	(0.495)
Mover: out of state	0.018	(0.132)	0.017	(0.13)	0.149	(0.356)
Mover: out of MSA	0.027	(0.162)	0.026	(0.159)	0.216	(0.411)
	N = 2,514,743		N = 251,474		N = 298,559	

Table 3: Key descriptive statistics: household microdata. Full sample includes all households with at least one member earning wages of at least $5000, and whose current (and previous, if applicable) residence falls in one of our study MSAs. Estimation sample is a 10% random draw of households from the full sample; this sample is used in most estimations involving microdata. Movers-only includes all households from the full sample who moved primary residence in the past year.

Least attractive MSAs	θ_j	MSAs with lowest churn	$\widehat{\epsilon_k}$
Parkersburg-Vienna, WV	-2.400	Parkersburg-Vienna, WV	-0.456
Columbus, IN	-2.235	Sebastian-Vero Beach, FL	-0.344
Kokomo, IN	-2.167	Kankakee, IL	-0.332
Kankakee, IL	-2.121	Monroe, MI	-0.332
Altoona, PA	-2.089	Dalton, GA	-0.326
Beckley, WV	-2.047	California-Lexington Park, MD	-0.306
Lebanon, PA	-2.034	Houston-The Woodlands-Sugar Land, TX	-0.303
Pittsfield, MA	-2.027	Altoona, PA	-0.294
East Stroudsburg, PA	-2.007	Johnstown, PA	-0.293
Johnstown, PA	-2.003	Kokomo, IN	-0.285
California-Lexington Park, MD	-1.971	Port St. Lucie, FL	-0.284
Williamsport, PA	-1.969	Deltona-Daytona Beach-Ormond Beach, FL	-0.274
Lima, OH	-1.969	Jackson, TN	-0.273
Sheboygan, WI	-1.945	North Port-Sarasota-Bradenton, FL	-0.271
Monroe, MI	-1.936	Cape Coral-Fort Myers, FL	-0.269
Kingston, NY	-1.858	Gainesville, GA	-0.263
Glens Falls, NY	-1.844	Punta Gorda, FL	-0.254
Dubuque, IA	-1.828	Michigan City-La Porte, IN	-0.252
Staunton-Waynesboro, VA	-1.824	Weirton-Steubenville-Wheeling, WV-OH	-0.240
Grand Island, NE	-1.821	Orlando-Kissimmee-Sanford-The Villages, FL	-0.240
Sumter, SC	-1.803	Lima, OH	-0.239
Madera, CA	-1.790	Hickory-Lenoir-Morganton, NC	-0.233
Gadsden, AL	-1.785	Lebanon, PA	-0.233
Jackson, TN	-1.784	Columbus, IN	-0.232
Mansfield, OH	-1.782	East Stroudsburg, PA	-0.232

Table 4: Stylized results from aggregate model (I). Left column lists the 25 MSAs with the smallest destination fixed effects (θ_j) resulting from our PPML gravity model estimation. Locations in Appalachia and the eastern Midwest abound. The right column lists the 25 MSAs with the smallest origin fixed effect, netting out the role of population ($\widehat{\varepsilon_k}$). Many names on the list look familiar, as unattractive places also tend to have low rates of out-migration. Additionally, we do note that many cities in Florida fall on this list - perhaps due to their heavy retirement populations.

Most attractive MSAs	θ_j	MSAs with highest churn	$\widehat{\epsilon_k}$
Houston-The Woodlands-Sugar Land, TX	1.026	Watertown-Fort Drum, NY	0.429
Dallas-Fort Worth-Arlington, TX	1.023	Ames, IA	0.378
Phoenix-Mesa-Scottsdale, AZ	0.952	Lawrence, KS	0.367
Atlanta-Sandy Springs-Roswell, GA	0.815	Amarillo, TX	0.333
Denver-...-Greeley, CO	0.800	Columbia, MO	0.308
Seattle-Tacoma-Bellevue, WA	0.761	Logan, UT-ID	0.299
Riverside-San Bernardino-Ontario, CA	0.686	Manhattan, KS	0.290
Miami-...-West Palm Beach, FL	0.635	San Diego-Carlsbad, CA	0.283
Los Angeles-Long Beach-Anaheim, CA	0.628	Clarksville, TN-KY	0.281
Chicago-Naperville-Elgin, IL-IN-WI	0.565	El Paso, TX	0.279
Tampa-St. Petersburg-Clearwater, FL	0.555	Great Falls, MT	0.272
Austin-Round Rock, TX	0.549	Missoula, MT	0.271
Orlando-...-The Villages, FL	0.548	Iowa City, IA	0.258
Las Vegas-Henderson-Paradise, NV	0.527	Lawton, OK	0.249
Washington-...-Alexandria, DC-VA-MD-WV	0.504	Las Cruces, NM	0.243
San Francisco-Oakland-Hayward, CA	0.494	Medford, OR	0.242
Portland-Vancouver-Hillsboro, OR-WA	0.465	Jacksonville-New Bern, NC	0.241
New York-Newark-Jersey City, NY-NJ-PA	0.463	Sioux Falls, SD	0.241
San Antonio-New Braunfels, TX	0.453	El Centro, CA	0.236
Boston-...-Nashua, MA-CT-NH	0.448	Lubbock, TX	0.230
Charlotte-Concord-Gastonia, NC-SC	0.368	Fayetteville, NC	0.225
Sacramento–Roseville–Arden-Arcade, CA	0.359	Ann Arbor, MI	0.218
Minneapolis-St. Paul-Bloomington, MN-WI	0.347	Cheyenne, WY	0.211
Philadelphia-...-Bridgeton, PA-NJ	0.341	Burlington-South Burlington, VT	0.211
Detroit-Warren-Dearborn, MI	0.253	New York-Newark-Jersey City, NY-NJ-PA	0.206

Table 5: Stylized results from aggregate model (II). Left column lists the 25 MSAs with the largest destination fixed effects (θ_j) resulting from our PPML gravity model estimation. Many Sun Belt cities top the list, but high-population coastal cities also rank high. The right column lists the 25 MSAs with the largest origin fixed effect, netting out the role of population ($\widehat{\varepsilon_k}$). Atop the list are a number of cities with a large university and military presence. Interspersed are a number of smaller cities in Mountain and Western states.

Panel A: 1st stage parameters	Estimate	S.E.
Income: Q1 (<22.2k)	0.3449	(0.0286)
Income: Q2 (<43.5k)	0.3264	(0.0675)
Income: Q3 (<68.8k)	0.2907	(0.0459)
Income: Q4 (<108.6k)	0.2052	(0.0298)
Income: Q5	0.1363	(0.0157)
MC: birth state	-1.0040	(0.0389)
MC: birth div	-0.4725	(0.0562)
MC: birth region	-0.2996	(0.049)
MC: kids	-0.7870	(0.0356)
MC: dual earners	-0.4592	(0.0591)
Housing quality	0.0581	(0.028)
Observations	251474	
Log-likelihood	-55513.01	

	[1]: OLS		[2]: IV1		[3]: IV2		[4]: IV3	
Panel B: 2nd stage parameters	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
Annual precipitation (mm)	-0.0003	(0.0001)	-0.0004	(0.0001)	-0.0004	(0.0001)	-0.0003	(0.0001)
Average winter temp. (°C)	0.0488	(0.0042)	0.0464	(0.0046)	0.0456	(0.0048)	0.0479	(0.005)
Average summer temp. (°C)	-0.0261	(0.0065)	-0.0220	(0.0073)	-0.0205	(0.0077)	-0.0246	(0.0081)
Average PM2.5 ($\mu g/m^3$)	-0.0170	(0.0075)	-0.0354	(0.0161)	-0.0421	(0.0185)	-0.0238	(0.0212)
Origin FEs	Yes		Yes		Yes		Yes	
Additional amenity controls	Yes		Yes		Yes		Yes	
Moving costs: distance	Yes		Yes		Yes		Yes	
Observations	44090		44090		44090		44090	

Table 6: Household-level location choice model: parameterizing the mean MWTP for amenities of interest. First stage parameters (Panel A) estimated by maximum likelihood. Income scaled by $10k in first stage. Second stage parameters (Panel B) estimated by generalized least squares, with observations weighted by origin population divided by size of origin's choice set. Standard errors are het-robust. Column 1 of Panel B does not instrument for PM2.5. Column 2 uses an instrument derived from distance- and wind-weighted summation of PM2.5 from neighboring MSAs in the destination's distance bandwidth. Column 3 uses an instrument derived from distance-weighted-only summation of PM2.5 from neighboring MSAs in the destination's distance bandwidth and NOT in the origin's choice set. Column 4 uses and instrument derived from distance- and wind-weighted summation of PM2.5 from neighboring MSAs in the destination's distance bandwidth and NOT in the origin's choice set.

	[1] Stock Model		[2] Stock Model: distance		[3] Flow Model	
	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
1st stage parameter estimates						
Income: Q1 (<22.2k)	0.4449	(0.0019)	0.4739	(0.0001)	0.3449	(0.286)
Income: Q2 (<$43.5k)	0.3367	(0.0017)	0.4312	(0.0033)	0.3264	(0.0675)
Income: Q3 (<$68.8k)	0.2777	(0.0037)	0.3482	(0.0115)	0.2907	(0.0459)
Income: Q4 (<$108.6k)	0.1672	(0.0042)	0.1810	(0.0961)	0.2052	(0.0298)
Income: Q5	0.0362	(0.0007)	0.1066	(0.0061)	0.1363	(0.0157)
2nd stage parameter estimates						
Annual precipitation (mm)	-0.0003	(0.0003)	-0.0010	(0.0004)	-0.0004	(0.0001)
Average winter temp. (°C)	0.0493	(0.0233)	0.0394	(0.0327)	0.0464	(0.0046)
Average summer temp. (°C)	-0.0163	(0.039)	0.0828	(0.0538)	-0.0220	(0.0073)
Average PM2.5 ($\mu g/m^3$)	0.0174	(0.0964)	-0.1610	(0.1232)	-0.0354	(0.0161)
ASCs identified from:	Population share		Population share		Origin migration share	
Housing Quality	Yes		Yes		Yes	
Additional amenity controls	Yes		Yes		Yes	
Moving Costs: birthplace	Yes		Yes		Yes	
Moving Costs: demographic	Yes		Yes		Yes	
Moving Costs: distance	No		Yes		Yes	
Origin FEs	No		No		Yes	
Log-likelihood (1st stage)	-401615.547		-83695.117		-55513.010	
Observations (1st stage)	251474		251474		251474	
Observations (2nd stage)	344		344		44090	

Table 7: Comparing the flow model to stock-based sorting models. First stage parameters estimated by maximum likelihood. Income scaled by $10k in first stage. Second stage parameters estimated by generalized least squares, with observations weighted by origin population divided by size of origin's choice set. In this table, we instrument for PM2.5 with an identical IV across specifications (see column 3 of Table 6). Standard errors are het-robust. Column [1] is a purely stock-based model in the spirit of the literature; ASCs are estimated for each destination, origin does not play a direct role. Column [2] includes distance-binned migration costs, but still estimates ASCs for only destinations. Column [3] is our flow model - identical to column [2] of Table 6.

	[1] Linear MU of income		[2] Log MU of income		[3] Sample: movers only	
	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
1st stage parameter estimates						
Income (linear)	0.1537	(0.017)				
log(Income)			0.6159	(0.0027)		
Income: Q1 (< 22.2k)					0.3258	(0.039)
Income: Q2 (< 43.5k)					0.3272	(0.0057)
Income: Q3 (<68.8k)					0.3112	(0.01)
Income: Q4 (< 108.6k)					0.2563	(0.0141)
Income: Q5					0.2208	(0.0143)
2nd stage parameter estimates						
Annual precipitation (mm)	-0.0004	(0.0001)	-0.0004	(0.0001)	-0.0003	(0.0001)
Average winter temp. (°C)	0.0482	(0.005)	0.0491	(0.005)	0.0476	(0.005)
Average summer temp. (°C)	-0.0251	(0.0081)	-0.0264	(0.008)	-0.0229	(0.008)
Average PM2.5 ($\mu g/m^3$)	-0.0277	(0.0211)	-0.0303	(0.0211)	-0.0340	(0.021)
Housing Quality	Yes		Yes		Yes	
Additional amenity controls	Yes		Yes		Yes	
Moving Costs: birthplace	Yes		Yes		Yes	
Moving Costs: demographic	Yes		Yes		Yes	
Moving Costs: distance	Yes		Yes		Yes	
Origin FEs	Yes		Yes		Yes	
Log-likelihood	-55522.108		-55526.845		-407820.188	
Observations (1st stage)	251474		251474		298559	
Observations (2nd stage)	44090		44090		44090	

Table 8: Robustness to alternative specifications and data. First stage parameters estimated by maximum likelihood. Income scaled by $10k in first stage in columns [1] and [3]. Second stage parameters estimated by generalized least squares, with observations weighted by origin population divided by size of origin's choice set. Instrument for average PM2.5 is preferred IV (see column [4] of Table 6). Column [1] imposes linear marginal utility (MU) of (net) income. Column [2] imposes log MU of income. Our preferred MU is a piecewise linear function by quintile. Column [3] studies estimates on a sample of only households that moved (either within- or between-MSAs) in the past year, using our preferred specification.

	[1] Winter Temp		[2] Summer Temp		[3] Precipitation		[4] PM2.5	
Panel A: HH preference heterogeneity	Estimate	S.E	Estimate	S.E	Estimate	S.E	Estimate	S.E
HH head college grad x ...	0.0332	(0.0082)	-0.0590	(0.0134)	-0.0239	(0.0116)	-0.0078	(0.0175)
HH head older than 55 x ...	0.0166	(0.0041)	-0.0369	(0.0091)	0.0050	(0.0102)	-0.0163	(0.0236)
HH head younger than 25 x ...	0.0242	(0.0238)	-0.0104	(0.0331)	-0.0292	(0.0313)	0.0120	(0.0502)
Children in HH x ...	0.0052	(0.0212)	-0.0102	(0.0749)	-0.0032	(0.0239)	0.0015	(0.1989)
Panel B: Homogenous HH parameters			Estimate				S.E.	
Income: Q1 (<22.2k)			0.3432				(0.0025)	
Income: Q2 (<43.5k)			0.3241				(0.011)	
Income: Q3 (<68.8k)			0.2861				(0.011)	
Income: Q4 (<108.6k)			0.1980				(0.0071)	
Income: Q5			0.1429				(0.0038)	
Panel C: Mean amenity preferences			Estimate				S.E.	
Annual precipitation (mm)			-0.0002				(0.0001)	
Average winter temp. (°C)			0.0234				(0.005)	
Average summer temp. (°C)			0.0224				(0.0081)	
Average PM2.5 ($\mu g/m^3$)			-0.0192				(0.0212)	
Housing Quality				Yes				
Additional amenity controls				Yes				
Moving Costs, birthplace				Yes				
Moving Costs, demographic				Yes				
Moving Costs, distance				Yes				
Origin FEs				Yes				
Log-likelihood				-55518.10				
1st stage observations				251474				
2nd stage observations				44090				

Table 9: HH heterogeneity in amenity preferences: note that this table shows results from a single model estimation. Panel A shows 16 parameter estimates for interactions of HH demographic characteristics and our environmental amenities of interest. Panel B shows parameter estimates for the marginal utility of income; this is uniform across household. Panel C shows parameter estimates for the baseline demographic group: a household with no children and a household head in the 25-54 age range without a college degree. First stage (panels A and B) estimated by maximum likelihood; second stage (panel C) estimated by generalized least squares with observations weighted by origin population divided by size of origin's choice set and using preferred IV for PM2.5. All standard errors het-robust.

	Quintile (at origin)	Estimate	S.E.	Implied MWTP*
	Q1	-0.0004	(0.0001)	-14.57
	Q2	-0.0004	(0.0001)	-12.08
Annual Precipitation	Q3	-0.0004	(0.0001)	-13.84
	Q4	-0.0003	(0.0001)	-10.33
	Q5	-0.0001	(0.0001)	-4.96
	Q1	0.0570	(0.0089)	1960.92
	Q2	0.0623	(0.0085)	2143.03
Average Winter Temperature	Q3	0.0597	(0.0132)	2053.45
	Q4	0.0347	(0.0065)	1193.08
	Q5	0.0330	(0.0075)	1136.83
	Q1	-0.0514	(0.0118)	-1767.55
	Q2	-0.0159	(0.0083)	-546.4
Average Summer Temperature	Q3	-0.0250	(0.009)	-860.12
	Q4	-0.0181	(0.0112)	-622.7
	Q5	-0.0244	(0.013)	-840.2
	Q1	-0.0112	(0.011)	-385.45
	Q2	-0.0398	(0.0109)	-1370.72
Mean PM2.5	Q3	-0.0406	(0.0089)	-1395.26
	Q4	-0.0196	(0.0097)	-675.16
	Q5	0.0040	(0.0157)	137.52
Additional amenity controls		Yes		
Moving Costs, all		Yes		
Origin FEs		Yes		

Table 10: Preference heterogeneity by origin. Here, we highlight second stage parameter estimates from a single model run. Destination amenity levels are interacted with quintile dummy variables for the origin's amenity level. This therefore studies how amenity preferences may vary with a household's previous previous/"status quo" level of the amenity. First stage parameters - and resulting ASCs used for estimation - are those from Table 6. Parameters estimated by generalized least squares, with observations weighted by origin population divided by size of origin's choice set. No instrument for PM2.5 in this regression. All standard errors are het-robust. *Implied MWTP shown for a household at the US median net income.

Appendix 1: Additional results

	Estimate	Implied MWTP ($)
Mean Net Income	0.426	
	(0.238)	
Annual Precipitation	-0.0003	-8.19
	(5.87e-05)	
Mean Winter Temperature	0.0195	457.75
	(0.005)	
Mean Summer Temperature	-0.0274	-643.19
	(0.008)	
Mean PM2.5	-0.0176	-413.15
	(0.008)	
Moving costs: distance	Yes	
Other amenity controls	Yes	
Origin FEs	Yes	
Observations	117648	

Table A1.1: Measures of MWTP for environmental amenities derived from an aggregate-data-only model. Estimation by Pseudo-Poisson Maximum Likelihood; standard errors are het-robust. Net income enters linearly in this stylized specification. MWTP is therefore a simple ratio of parameters.

	ln(wage income)		ln(price)		ln(rent)		prob(ownership)	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Age	0.071	0.010	0.008	0.010	-0.001	0.010	0.072	0.022
Age^2	-0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000
HS diploma	0.226	0.052	0.131	0.107	0.077	0.077	0.213	0.175
College grad	0.467	0.081	0.246	0.129	0.135	0.092	0.317	0.204
Grad school	0.713	0.058	0.266	0.139	0.157	0.108	0.193	0.245
Female	-0.194	0.039	-0.010	0.032	0.005	0.034	0.003	0.078
Married	0.117	0.032	0.208	0.063	0.080	0.052	0.598	0.124
Sep/div/widowed			0.101	0.063	0.034	0.044	-0.010	0.104
Hispanic	-0.056	0.077	-0.050	0.130	-0.031	0.088	-0.192	0.254
Black	-0.137	0.105	0.043	0.179	-0.038	0.103	-0.724	0.781
Other nonwhite	-0.053	0.071	-0.035	0.132	-0.022	0.080	-0.303	0.255
Dahl prob	-0.022	0.424						
Dahl prob^2	0.013	0.686						
Job prestige (Sieg.)			0.004	0.001	0.002	0.001	0.006	0.003
HH income			0.000	0.000	0.000	0.000	0.000	0.000
# of HH earners			-0.015	0.035	0.070	0.041	-0.011	0.077
# of HH children			0.046	0.026	0.047	0.026	0.001	0.066
MSA Count	344		344		344		344	
Industry FEs	Yes							
Occupation FEs	Yes							
Year FEs	Yes		Yes		Yes		Yes	
Weekly hours worked (bin)	Yes		Yes		Yes		Yes	
Observation level	Individual		Household (head)		Household (head)		Household (head)	

Table A1.2: Summary of counterfactual income and housing expenditure regression parameters. Separate hedonic (wage income, owned housing prices, rental prices) and ownership probability regressions were run in each of $N = 344$ MSAs. We summarize the resulting distribution of parameter estimates for each characteristic by the mean and standard deviation of values across MSAs. All money measures were deflated by yearly CPI.

	Outer bandwidth									
	500km		750km		1000km		1250km		1500km	
Inner bandwidth	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
50km	-0.0946	(0.0183)	-0.0584	(0.0193)	-0.0416	(0.02)	-0.0362	(0.021)	-0.0331	(0.0212)
75km	-0.1003	(0.0183)	-0.0614	(0.0194)	-0.0435	(0.0201)	-0.0378	(0.0212)	-0.0346	(0.0215)
100km	-0.0809	(0.0193)	-0.0412	(0.0205)	-0.0238	(0.0212)	-0.0180	(0.0224)	-0.0146	(0.0227)
125km	-0.0765	(0.0193)	-0.0351	(0.0207)	-0.0174	(0.0214)	-0.0114	(0.0227)	-0.0079	(0.023)
150km	-0.0406	(0.0199)	-0.0037	(0.0213)	0.0111	(0.0221)	0.0170	(0.0235)	0.0205	(0.0239)

Table A1.3: Robustness: instrument sensitivity to distance bandwidths. Inner bandwidth is the lower distance bound for a neighboring MSA's PM2.5 level to be included in the instrument's generation. Similarly, outer bandwidth is the upper distance bound. The displayed PM2.5 parameter estimates and standard errors come from the second stage model as in Table 6; the only things changing are the distance bandwidths used to generate the instrument.

Appendix 2: Description of migration flow and household microdata

To infer household willingness-to-pay for urban amenities, our model jointly relies on (1) aggregate-level data on migration flows between metropolitan statistical areas (MSAs) and (2) micro-level data that provides household-level location choices, income, and housing expenditures, as well as demographic information we can leverage to understanding heterogeneity in preferences. In what follows, we describe these data and explain the decisions we took during their preparation and cleaning.

The aggregate MSA-to-MSA migration flow data come directly from the Census Bureau. We use the 2012-2016 vintage, which was constructed from 1-year American Community Survey (ACS) samples over that time period. Our flow measure is the Bureau's point estimate of the annual count of individuals who moved between given MSAs during the past year; thus, the measure is effectively a 5-year average of the origin-destination pair's gross annual migration flow. While this is an estimate based on a 5% population sample, we prefer this data to the IRS's tax-filing-generated migration data for three main reasons. First, because our model is cross-sectional in nature, we have little interest in constructing a year-over-year panel of migration flows, which is the main advantage of the IRS data. Second, the IRS data has well-noted sample selection issues: household that don't file taxes (read: poor or elderly) or file complicated taxes after the standard filing deadline (read: wealthy) are not counted. Third, the IRS data is heavily censored from the left; migration flows of fewer than 10 households are suppressed, painting an less complete picture of migration patterns. As zero flows between MSAs cannot be identified by our model, we find this systematic censoring especially unattractive.

Our household microdata is a 5-year (2012-2016) public-use ACS sample curated by the much-heralded IPUMS USA (Ruggles et al, 2020). While this ACS product is also the original source of our aggregate MSA-MSA flows, in its public-use micro-data form, confidentiality measures have been taken in terms of geographic information. For the unfamiliar, we discuss the ramifications of these confidentiality measures below in some detail, but the key implication is that one cannot recreate or replicate the Census Bureau's point estimates of MSA-to-MSA migration flows directly from the publicly-available microdata. Hence our reliance on the separate data product for aggregate migration flow counts. In the microdata, households' current residential geography is assigned by Public Use Microdata Area (PUMA), while their previous residential geography is assigned by Migration PUMA (MIGPUMA). PUMA geographies are nested in MIGPUMAs. PUMAs are built from counties and census tracts, comprising of populations roughly on the order of 100,000. MIGPUMAs correspond to exactly one or more PUMAs, often resulting in aggregated geographies that contain larger populations.

MSAs are constructed from counties. As a result, for households we observe residing in a PUMA that crosses an MSA boundary, it is not possible to assign the correct geography with certainty. Resulting misassignment errors are typically small, and in our experience, almost universally ignored in similar empirical social science applications. However, these assignment errors may compound when incorporating MIGPUMAs, since their geographic footprint may be substantially larger. As we are unaware of any previous work using this MIGPUMA variable in the locational sorting literature, we proceed by the following data construction procedure. This undertaking, of course, has our modelling application in mind and may be more or less appropriate in other settings.

Our objective in constructing the microdata sample is to maintain as many potential origin/destination MSAs as possible for our second-stage estimation, while balancing a desire to obtain unbiased first-stage estimation parameters. To determine which households are included in our estimation sample, the following rules/practices are adopted in our MIGPUMA assignment procedure.

1. We assign MIGPUMAs to MSAs by broadly attempting to minimize total error rate (sum of commission and omission rates, see below for fuller definition) that results from inclusion. When possible, we prefer assignment errors of omission to assignment errors of commission. In several cases, this results in a higher total error rate, but zero commission error rate.

2. Total error rates greater than the arbitrary value of 50% result in an MSA being dropped from our sample. This results in the loss of 14 MSAs, representing the roughly 2.46% of the urban-based population in the continental US. These MSAs are displayed in Table A2.1.

3. When possible, we create "hybrid-MSAs" in order to avoid dropping high-error-rate MSAs from our sample. These are spatial joins of neighboring MSAs where MIGPUMA boundaries make it impossible to differentiate a household's true origin MSA. For our intended purpose of valuing air quality and climate, these MSAs are likely to be similar in key characteristics, though we do lose a little bit of usable variation. In total, we map 35 MSAs into 16 "hybrid-MSAs".

4. For all cases of commission error, we make sure that the MIGPUMA in question only contains rural counties or micropolitan statistical areas. If an offending MIGPUMA spans two MSAs, we either create a "hybrid-MSA" or drop the MIGPUMA's households from the sample. Thus, we never misclassify a household's origin in the sense of assigning them to one MSA when they truly resided in a different MSA.

Our resulting MIGPUMA-to-MSA assignment results in each MSA falling into one of four descriptive classes:

1. Perfect match: MIGPUMA and MSA geographies align perfectly, resulting in a 100% match of an MSA's households to their true origin MSA. (Geography count: 150 / 344)

2. Some omission occurring: All households assigned to an origin MSA by our procedure did previously reside in the true geographic boundaries of that MSA. However, some percentage of true residents are omitted because MIGPUMA boundaries cross the MSA borders. (Geography count: 117 / 344)

3. Some commission occurring: 100% of households who did previously reside in an origin MSA are assigned the correct geography, but additional households are also assigned to that origin. These additional households did not truly reside in the MSA's boundaries, but their MIGPUMA's borders surpass those of the MSA. (Geography count: 60 / 344)

4. Both omission and commission occurring: some percentage of the origin MSA's true residents are omitted from our resulting sample, and some additional, non-origin-MSA resident households are committed. (Geography count: 17 / 344)

A summary of destination and origin assignment error rates for included MSAs is found below in table A2.2.

MSA Title	Population
Brunswick, GA	112370
Carson City, NV	55274
Danville, IL	81625
Elmira, NY	88830
Florence-Muscle Shoals, AL	147137
Grand Forks, ND-MN	98461
Grants Pass, OR	82713
Jonesboro, AR	121026
Lewiston, ID-WA	60888
Morristown, TN	113951
Pine Bluff, AR	100258
Pocatello, ID	82839
Pueblo, CO	159063
Sebring, FL	98786

Table A2.1: MSAs omitted from our study due to PUMA/MIGPUMA-MSA boundary issues in the microdata.

Table A2.2: Summary list of MSAs included in analysis

		Destination error (%)			Origin error (%)		
MSA Name (* denotes merge of >1 MSAs)	Population	Omission	Commission	Total	Omission	Commission	Total
Abilene, TX	165252	20.42	0	20.42	20.42	0	20.42
Akron, OH	703200	0	0	0	0	0	0
Albany, GA	157308	21.9	0	21.9	21.9	0	21.9
Albany-Corvallis, OR*	202251	0	0	0	0	0	0
Albany-Schenectady-Troy, NY	870716	3.76	0	3.76	3.76	0	3.76
Albuquerque, NM	887077	1.85	0	1.85	1.85	0	1.85
Alexandria, LA	153922	14.49	28.45	42.94	14.49	28.45	42.94
Allentown-Bethlehem-Easton, PA-NJ	821173	0	0	0	0	0	0
Altoona, PA	127089	0	26.54	26.54	0	26.54	26.54
Amarillo, TX	251933	4.02	0	4.02	4.02	0	4.02
Ames, IA	89542	0	22.71	22.71	0	22.71	22.71
Ann Arbor, MI	344791	0	0	0	0	0	0
Anniston-Oxford-Jacksonville, AL	118572	0	0	0	0	0	0
Appleton-Fond du Lac, WI*	327299	0	0	0	0	0	0
Asheville, NC	424858	43.91	0	43.91	43.91	0	43.91
Athens-Clarke County, GA	192541	39.38	0	39.38	39.38	0	39.38
Atlanta-Sandy Springs-Roswell, GA	5286728	5.82	0	5.82	5.82	0	5.82
Atlantic City-Hammonton-Ocean City, NJ*	371814	0	0	0	0	0	0
Auburn-Opelika, AL	140247	0	0	0	0	0	0
Augusta-Richmond County, GA-SC	564873	9.42	0	9.42	9.42	0	9.42
Austin-Round Rock, TX	1716289	6.54	0	6.54	6.54	0	6.54
Bakersfield, CA	839631	0	0	0	0	0	0
Baltimore-Columbia-Towson, MD	2710489	1.76	0	1.76	1.76	0	1.76
Bangor, ME	153923	0	0	0	0	0	0
Barnstable Town, MA	215888	39.25	0	39.25	0	11.01	11.01
Baton Rouge, LA	802484	0	0	0	0	0	0
Battle Creek, MI	136146	0	30.3	30.3	0	30.3	30.3
Bay City-Midland, MI*	191400	0	0	0	0	0	0
Beaumont-Port Arthur, TX	403190	3.58	0	3.58	3.58	0	3.58
Beckley, WV	124898	0	33.27	33.27	0	33.27	33.27
Bellingham, WA	201140	0	0	0	0	0	0
Bend-Redmond, OR	157733	0	0	0	0	0	0
Billings, MT	158934	34.9	0	34.9	6.34	39.18	45.52
Binghamton, NY	251725	5.53	0	5.53	0	28.12	28.12
Birmingham-Hoover, AL	1128047	11.84	0	11.84	11.84	0	11.84
Bismarck, ND	114778	5.23	9.02	14.25	5.23	9.02	14.25
Blacksburg-Christiansburg-Radford, VA	178237	0	0	0	0	0	0

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MSA Name (* denotes merge of >1 MSAs)	Population	Destination error (%) Omission	Commission	Total	Origin error (%) Omission	Commission	Total
Bloomington, IL	186133	8.9	0	8.9	8.9	0	8.9
Bloomington, IN	159549	13.52	0	13.52	13.52	0	13.52
Bloomsburg-...-Hazleton, PA*	649193	2.81	0	2.81	0	12.71	12.71
Boise City, ID	616561	12.99	0	12.99	1.14	5.11	6.25
Boston-...-Nashua, MA-CT-NH*	5870103	2.41	0.33	2.74	0	12.03	12.03
Bowling Green, KY	158599	28.25	0	28.25	28.25	0	28.25
Bremerton-Silverdale, WA	251133	0	0	0	0	0	0
Bridgeport-Stamford-Norwalk, CT	916829	0	0	0	0	0	0
Brownsville-Harlingen, TX	406220	0	0	0	0	0	0
Buffalo-Cheektowaga-Niagara Falls, NY	1135509	0	0	0	0	0	0
Burlington, NC	151131	0	0	0	0	0	0
Burlington-South Burlington, VT	211261	0	0	0	0	0	0
California-Lexington Park, MD	105151	0	45.77	45.77	0	45.77	45.77
Canton-Massillon, OH	404422	0	0	0	0	0	0
Cape Coral-Fort Myers, FL	618754	0	0	0	0	0	0
Cape Girardeau, MO-IL	96275	8.56	30.8	39.36	8.56	30.8	39.36
Carbondale-Marion, IL	126575	0	32.85	32.85	0	32.85	32.85
Casper, WY	75450	0	28.26	28.26	0	28.26	28.26
Cedar Rapids, IA	257940	18.11	0	18.11	18.11	0	18.11
Chambersburg-Waynesboro-Gettysburg, PA*	251025	0	0	0	0	0	0
Champaign-Urbana, IL	231891	13.29	0	13.29	13.29	0	13.29
Charleston, WV	227078	10.85	0	10.85	10.85	0	10.85
Charleston-North Charleston, SC	664607	0	0	0	0	0	0
Charlotte-Concord-Gastonia, NC-SC	2217012	15.68	0	15.68	23.7	0	23.7
Charlottesville, VA	218705	7.84	14.12	21.96	7.84	14.12	21.96
Chattanooga, TN-GA	528143	8.02	5.08	13.1	8.02	5.08	13.1
Cheyenne, WY	91738	0	28.35	28.35	0	28.35	28.35
Chicago-Naperville-Elgin, IL-IN-WI	9461105	0.5	0	0.5	0.5	0	0.5
Chico, CA	220000	0	0	0	0	0	0
Cincinnati, OH-KY-IN	2114580	9.96	0	9.96	9.96	0	9.96
Clarksville, TN-KY	260625	0	11.57	11.57	0	11.57	11.57
Cleveland, TN	115788	0	31.1	31.1	0	31.1	31.1
Cleveland-Elyria, OH	2077240	0	0	0	0	0	0
Coeur d'Alene, ID	138494	3.5	0	3.5	0	44.52	44.52
College Station-Bryan, TX	228660	14.79	0	14.79	14.79	0	14.79
Colorado Springs, CO	645613	0	0	0	0	0	0
Columbia, MO	162642	0	0	0	0	0	0
Columbia, SC	767598	0	0	0	0	0	0
Columbus, GA-AL	294865	31.78	0	31.78	31.78	0	31.78

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MSA Name (* denotes merge of >1 MSAs)	Population	Destination error (%) Omission	Commission	Total	Origin error (%) Omission	Commission	Total
Columbus, IN	76794	0	35.56	35.56	0	35.56	35.56
Columbus, OH	1901974	5.27	0	5.27	5.27	0	5.27
Corpus Christi, TX	428185	20.54	0	20.54	20.54	0	20.54
Crestview-...-Panama City, FL*	420580	3.77	9.63	13.4	3.77	9.63	13.4
Cumberland-...-Winchester, MD-WV-VA*	483370	0	19.24	19.24	0	19.24	19.24
Dallas-Fort Worth-Arlington, TX	6426214	1.85	0	1.85	1.85	0	1.85
Dalton, GA	142227	27.86	0	27.86	27.86	0	27.86
Daphne-Fairhope-Foley, AL	182265	0	0	0	0	0	0
Davenport-Moline-Rock Island, IA-IL	379690	17.62	0	17.62	17.62	0	17.62
Dayton, OH	799232	0	0	0	0	0	0
Decatur, AL	153829	0	0	0	0	0	0
Decatur, IL	110768	0	0	0	0	0	0
Deltona-Daytona Beach-Ormond Beach, FL	590289	0	0	0	0	0	0
Denver-Aurora-Lakewood-Boulder-Greeley, CO*	3090874	0.8	0	0.8	0.52	3.19	3.71
Des Moines-West Des Moines, IA	569633	16.44	0	16.44	1.92	11.16	13.08
Detroit-Warren-Dearborn, MI	4296250	2.06	0	2.06	2.06	0	2.06
Dothan, AL	145639	0	25.65	25.65	0	25.65	25.65
Dover, DE	162310	0	0	0	0	0	0
Dubuque, IA	93653	0	38.48	38.48	0	38.48	38.48
Duluth, MN-WI	279771	15.78	33.59	49.37	15.78	33.59	49.37
Durham-Chapel Hill, NC	504357	20.42	0	20.42	20.42	0	20.42
East Stroudsburg, PA	169842	0	0	0	0	0	0
Eau Claire, WI	161151	5.52	0	5.52	0	43.64	43.64
El Centro, CA	174528	0	0	0	0	0	0
El Paso, TX	804123	0.43	0	0.43	0.43	0	0.43
Elizabethtown-Fort Knox, KY	148338	21.53	28.24	49.77	0	44.88	44.88
Elkhart-Goshen, IN	197559	0	0	0	0	0	0
Erie, PA	280566	0	0	0	0	0	0
Eugene, OR	351715	0	0	0	0	0	0
Evansville, IN-KY	311552	42.32	0	42.32	42.32	0	42.32
Fargo, ND-MN	208777	28.26	0	28.26	28.26	0	28.26
Farmington, NM	130044	22.38	0	22.38	0	43.15	43.15
Fayetteville, NC	366383	12.82	0	12.82	12.82	0	12.82
Fayetteville-Springdale-Rogers, AR-MO	463204	8.38	0	8.38	8.38	0	8.38
Flagstaff, AZ	134421	0	0	0	0	0	0
Flint, MI	425790	0	27.19	27.19	0	27.19	27.19
Florence, SC	205566	0	0	0	0	0	0
Fort Collins, CO	299630	0	0	0	0	0	0
Fort Smith, AR-OK	280467	33.08	0	33.08	33.08	0	33.08

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MSA Name (* denotes merge of >1 MSAs)	Population	Destination error (%) Omission	Destination error (%) Commission	Destination error (%) Total	Origin error (%) Omission	Origin error (%) Commission	Origin error (%) Total
Fort Wayne, IN	416257	14.64	0	14.64	14.64	0	14.64
Fresno, CA	930450	0	0	0	0	0	0
Gadsden, AL	104430	0	0	0	0	0	0
Gainesville, FL	264275	6.41	0	6.41	6.41	0	6.41
Gainesville, GA	179684	0	0	0	0	0	0
Glens Falls, NY	128923	0	0	0	0	0	0
Goldsboro, NC	122623	0	0	0	0	0	0
Grand Island, NE	81850	0	23.3	23.3	0	23.3	23.3
Grand Junction, CO	146723	12.15	0	12.15	0	36.41	36.41
Grand Rapids-Wyoming, MI	988938	12.39	0	12.39	12.39	0	12.39
Great Falls, MT	81327	0	44.99	44.99	0	44.99	44.99
Green Bay, WI	306241	19.02	0	19.02	19.02	0	19.02
Greensboro-High Point, NC	723801	12.94	0	12.94	12.94	0	12.94
Greenville, NC	168148	0	0	0	0	0	0
Greenville-Anderson-Mauldin, SC	824112	14.47	0	14.47	14.47	0	14.47
Gulfport-Biloxi-Pascagoula, MS	370702	11.85	0	11.85	11.85	0	11.85
Hammond, LA	121097	0	28.03	28.03	0	28.03	28.03
Hanford-Corcoran, CA	152982	0	0	0	0	0	0
Harrisburg-Carlisle, PA	549475	0	0	0	0	0	0
Harrisonburg, VA	125228	0	0	0	0	0	0
Hartford-West Hartford-East Hartford, CT	1212381	0	0	0	0	0	0
Hattiesburg, MS	142842	0	15.94	15.94	0	15.94	15.94
Hickory-Lenoir-Morganton, NC	365497	24.87	0	24.87	24.87	0	24.87
Hilton Head Island-Bluffton-Beaufort, SC	187010	0	0	0	0	0	0
Hinesville-Savannah, GA*	425528	12.28	0	12.28	12.28	0	12.28
Homosassa Springs, FL	141236	0	0	0	0	0	0
Hot Springs, AR	96024	0	40.52	40.52	0	40.52	40.52
Houma-Thibodaux, LA	208178	0	10.11	10.11	0	10.11	10.11
Houston-The Woodlands-Sugar Land, TX	5920416	1.21	0	1.21	1.21	0	1.21
Huntington-Ashland, WV-KY-OH	364908	17.11	25.47	42.58	17.11	25.47	42.58
Huntsville, AL	417593	6.06	0	6.06	0	18.22	18.22
Idaho Falls, ID	133265	21.78	0	21.78	21.78	0	21.78
Indianapolis-Carmel-Anderson, IN	1887877	0	0	0	0	0	0
Iowa City, IA	152586	14.22	0	14.22	14.22	0	14.22
Ithaca, NY	101564	0	0	0	0	0	0
Jackson, MI	160248	0	0	0	0	0	0
Jackson, MS	567122	9.96	0	9.96	0	7.92	7.92
Jackson, TN	130011	11.22	0	11.22	11.22	0	11.22
Jacksonville, FL	1345596	1.96	0	1.96	14.12	0	14.12

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MSA Name (* denotes merge of >1 MSAs)	Population	Destination error (%) Omission	Commission	Total	Origin error (%) Omission	Commission	Total
Jacksonville-New Bern, NC*	304574	4.32	16.34	20.66	4.32	16.34	20.66
Janesville-Beloit, WI	160331	0	0	0	0	0	0
Jefferson City, MO	149807	0	0	0	0	0	0
Johnson City, TN	198716	38.11	0	38.11	38.11	0	38.11
Johnstown, PA	143679	0	0	0	0	0	0
Joplin, MO	175518	0	0	0	0	0	0
Kalamazoo-Portage, MI	326589	23.35	0	23.35	23.35	0	23.35
Kankakee, IL	113449	0	0	0	0	0	0
Kansas City, MO-KS	2009342	10.24	0	10.24	10.24	0	10.24
Killeen-Temple, TX	405300	23.46	0	23.46	23.46	0	23.46
Kingsport-Bristol-Bristol, TN-VA	309544	30.98	0	30.98	30.98	0	30.98
Kingston, NY	182493	18.99	0	18.99	0	29.82	29.82
Knoxville, TN	837571	22.46	0	22.46	22.46	0	22.46
Kokomo, IN	82752	0	39.88	39.88	0	39.88	39.88
La Crosse-Onalaska, WI-MN	133665	14.23	0	14.23	14.23	0	14.23
Lafayette, LA	466750	26.87	0	26.87	26.87	0	26.87
Lafayette-West Lafayette, IN	201789	14.38	0	14.38	14.38	0	14.38
Lake Charles, LA	199607	0	31.79	31.79	0	31.79	31.79
Lake Havasu City-Kingman, AZ	200186	0	9.28	9.28	0	9.28	9.28
Lakeland-Winter Haven, FL	602095	0	0	0	0	0	0
Lancaster, PA	519445	0	0	0	0	0	0
Lansing-East Lansing, MI	464036	0	0	0	0	0	0
Laredo, TX	250304	0	0	0	0	0	0
Las Cruces, NM	209233	0	0	0	0	0	0
Las Vegas-Henderson-Paradise, NV	1951269	0	0	0	0	0	0
Lawrence, KS	110826	0	0	0	0	0	0
Lawton, OK	130291	18.42	0	18.42	0	40.62	40.62
Lebanon, PA	133568	0	0	0	0	0	0
Lewiston-Auburn, ME	107702	0	0	0	0	0	0
Lexington-Fayette, KY	472099	37.34	0	37.34	37.34	0	37.34
Lima, OH	106331	0	0	0	0	0	0
Lincoln, NE	302157	5.54	0	5.54	5.54	0	5.54
Little Rock-North Little Rock-Conway, AR	699757	4.04	0	4.04	4.04	0	4.04
Logan, UT-ID	125442	10.19	29.9	40.09	10.19	29.9	40.09
Longview, TX	214369	43.21	0	43.21	43.21	0	43.21
Longview, WA	102410	0	19.56	19.56	0	19.56	19.56
Los Angeles-Long Beach-Anaheim, CA	12828837	0	0	0	0	0	0
Louisville/Jefferson County, KY-IN	1235708	1.96	0	1.96	1.96	0	1.96
Lubbock, TX	290805	4.12	0	4.12	4.12	0	4.12

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Lynchburg, VA	252634	0	0	0	0	0	0
Macon, GA	232293	33.04	0	33.04	33.04	0	33.04
Madera, CA	150865	0	0	0	0	0	0
Madison, WI	605435	19.38	0	19.38	19.38	0	19.38
Manhattan, KS	92719	0	27.04	27.04	0	27.04	27.04
Mankato-North Mankato, MN	96740	0	16.51	16.51	0	16.51	16.51
Mansfield, OH	124475	0	0	0	0	0	0
McAllen-Edinburg-Mission, TX	774769	0	0	0	0	0	0
Medford, OR	203206	0	0	0	0	0	0
Memphis, TN-MS-AR	1324829	17.81	0	17.81	17.81	0	17.81
Merced, CA	255793	0	0	0	0	0	0
Miami-Fort Lauderdale-West Palm Beach, FL	5564635	0.51	0	0.51	0	1.3	1.3
Michigan City-La Porte, IN	111467	0	0	0	0	0	0
Midland, TX	141671	3.39	0	3.39	3.39	0	3.39
Milwaukee-Waukesha-West Allis, WI	1555908	0	0	0	0	0	0
Minneapolis-St. Paul-Bloomington, MN-WI	3348859	11.19	0	11.19	11.19	0	11.19
Missoula, MT	109299	0	43.63	43.63	0	43.63	43.63
Mobile, AL	412992	0	0	0	0	0	0
Modesto, CA	514453	0	0	0	0	0	0
Monroe, LA	176441	12.88	0	12.88	12.88	0	12.88
Monroe, MI	152021	0	0	0	0	0	0
Montgomery, AL	374536	0	0	0	0	0	0
Morgantown, WV	129709	0	0	0	0	0	0
Mount Vernon-Anacortes, WA	116901	0	44.64	44.64	0	44.64	44.64
Muncie, IN	117671	0	0	0	0	0	0
Muskegon, MI	172188	0	0	0	0	0	0
Myrtle Beach-Conway-North Myrtle Beach, SC-NC	376722	0	0	0	0	0	0
Napa, CA	136484	0	0	0	0	0	0
Naples-Immokalee-Marco Island, FL	321520	0	0	0	0	0	0
Nashville-Davidson–Murfreesboro–Franklin, TN	1670890	8.62	0	8.62	8.62	0	8.62
New Haven-Milford, CT	862477	0	0	0	0	0	0
New Orleans-Metairie, LA	1189866	0	0	0	0	0	0
New York-Newark-Jersey City, NY-NJ-PA	19567410	0.29	0	0.29	0.29	0	0.29
Niles-Benton Harbor, MI	156813	0	0	0	0	0	0
North Port-Sarasota-Bradenton, FL	702281	0	0	0	0	0	0
Norwich-New London, CT	274055	0	0	0	0	0	0
Ocala, FL	331298	0	0	0	0	0	0
Odessa, TX	137130	0	0	0	0	0	0
Ogden-Clearfield, UT	597159	9.95	0	9.95	9.95	0	9.95

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Oklahoma City, OK	1252987	13.01	0	13.01	13.01	0	13.01
Olympia-Tumwater, WA	252264	0	0	0	0	0	0
Omaha-Council Bluffs, NE-IA	865350	21.89	0	21.89	21.89	0	21.89
Orlando-Kissimmee-Sanford-The Villages, FL*	2227831	0	0	0	0	0	0
Oshkosh-Neenah, WI	166994	0	0	0	0	0	0
Owensboro, KY	114752	8.31	0	8.31	8.31	0	8.31
Oxnard-Thousand Oaks-Ventura, CA	823318	0	0	0	0	0	0
Palm Bay-Melbourne-Titusville, FL	543376	0	0	0	0	0	0
Parkersburg-Vienna, WV	92673	0	7.58	7.58	0	7.58	7.58
Pensacola-Ferry Pass-Brent, FL	448991	0	0	0	0	0	0
Peoria, IL	379186	15.11	0	15.11	15.11	0	15.11
Philadelphia-...-Vineland-Bridgeton, PA-NJ*	6122241	0	0	0	0	0	0
Phoenix-Mesa-Scottsdale, AZ	4192887	0.26	0	0.26	8.96	0	8.96
Pittsburgh, PA	2356285	6.39	0	6.39	18.98	0	18.98
Pittsfield, MA	131219	0	0	0	0	0	0
Port St. Lucie, FL	424107	0	0	0	0	0	0
Portland-South Portland, ME	514098	0	0	0	0	0	0
Portland-Vancouver-Hillsboro, OR-WA	2226009	7.17	0	7.17	7.17	0	7.17
Prescott, AZ	211033	0	0	0	0	0	0
Providence-Warwick, RI-MA	1600852	12.83	0	12.83	34.25	0	34.25
Provo-Orem, UT	526810	1.94	0	1.94	1.94	0	1.94
Punta Gorda, FL	159978	0	0	0	0	0	0
Racine, WI	195408	0	0	0	0	0	0
Raleigh, NC	1130490	5.36	0	5.36	5.36	0	5.36
Rapid City, SD	134598	0	22.22	22.22	0	22.22	22.22
Reading, PA	411442	0	0	0	0	0	0
Redding, CA	177223	0	0	0	0	0	0
Reno, NV	425417	0.94	0	0.94	0.94	0	0.94
Richmond, VA	1208101	15.68	0	15.68	15.68	0	15.68
Riverside-San Bernardino-Ontario, CA	4224851	0	0	0	0	0	0
Roanoke, VA	308707	0	6.71	6.71	0	6.71	6.71
Rochester, MN	206877	30.27	0	30.27	30.27	0	30.27
Rochester, NY	1079671	18.71	0	18.71	18.71	0	18.71
Rockford, IL	349431	0	0	0	0	0	0
Rocky Mount, NC	152392	0	0	0	0	0	0
Rome, GA	96317	0	42.18	42.18	0	42.18	42.18
Sacramento–Roseville–Arden-Arcade, CA	2149127	0	0	0	0	0	0
Saginaw, MI	200169	0	0	0	0	0	0
Salem, OR	390738	19.3	0	19.3	19.3	0	19.3

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MSA Name (* denotes merge of >1 MSAs)	Population	Destination error (%) Omission	Commission	Total	Origin error (%) Omission	Commission	Total
Salinas, CA	415057	18.52	0	18.52	0	11.75	11.75
Salisbury, MD-DE	373802	0	0	0	0	0	0
Salt Lake City, UT	1087873	5.35	0	5.35	5.35	0	5.35
San Angelo, TX	111823	1.43	0	1.43	1.43	0	1.43
San Antonio-New Braunfels, TX	2142508	8.76	0	8.76	8.76	0	8.76
San Diego-Carlsbad, CA	3095313	0	0	0	0	0	0
San Francisco-Oakland-Hayward, CA	4335391	0	0	0	0	0	0
San Jose-Sunnyvale-Santa Clara, CA	1836911	3.01	0	3.01	3.01	0	3.01
San Luis Obispo-Paso Robles-Arroyo Grande, CA	269637	0	0	0	0	0	0
Santa Cruz-Watsonville, CA	262382	0	0	0	0	0	0
Santa Fe, NM	144170	0	0	0	0	0	0
Santa Maria-Santa Barbara, CA	423895	0	0	0	0	0	0
Santa Rosa, CA	483878	0	0	0	0	0	0
Seattle-Tacoma-Bellevue, WA	3439809	0	0	0	0	0	0
Sebastian-Vero Beach, FL	138028	0	0	0	0	0	0
Sheboygan, WI	115507	0	0	0	0	0	0
Sherman-Denison, TX	120877	0	37.44	37.44	0	37.44	37.44
Shreveport-Bossier City, LA	439811	6.06	0	6.06	6.06	0	6.06
Sierra Vista-Douglas, AZ	131346	0	26.53	26.53	0	26.53	26.53
Sioux City, IA-NE-SD	168563	24.56	0	24.56	24.56	0	24.56
Sioux Falls, SD	228261	0	18.17	18.17	0	18.17	18.17
South Bend-Mishawaka, IN-MI	319224	16.38	0	16.38	16.38	0	16.38
Spartanburg, SC	313268	9.24	0	9.24	9.24	0	9.24
Spokane-Spokane Valley, WA	527753	10.71	0	10.71	10.71	0	10.71
Springfield, IL	210170	6.05	0	6.05	6.05	0	6.05
Springfield, MA	621570	8.1	0	8.1	0	10.3	10.3
Springfield, MO	436712	10.97	0	10.97	10.97	0	10.97
Springfield, OH	138333	0	0	0	0	0	0
St. Cloud, MN	189093	20.33	0	20.33	20.33	0	20.33
St. George, UT	138115	0	0	0	0	0	0
St. Joseph, MO-KS	127329	6.24	0	6.24	6.24	0	6.24
St. Louis, MO-IL	2787701	8.95	0	8.95	8.95	0	8.95
State College, PA	153990	0	0	0	0	0	0
Staunton-Waynesboro, VA	118502	0	26.65	26.65	0	26.65	26.65
Stockton-Lodi, CA	685306	0	0	0	0	0	0
Sumter, SC	107456	0	45.2	45.2	0	45.2	45.2
Syracuse, NY	662577	16.4	0	16.4	11.08	11.96	23.04
Tallahassee, FL	367413	25.02	0	25.02	25.02	0	25.02
Tampa-St. Petersburg-Clearwater, FL	2783243	0	0	0	0	0	0

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MSA Name (* denotes merge of >1 MSAs)	Population	Destination error (%)			Origin error (%)		
		Omission	Commission	Total	Omission	Commission	Total
Terre Haute, IN	172425	37.45	0	37.45	37.45	0	37.45
Texarkana, TX-AR	149198	0	35.19	35.19	0	35.19	35.19
Toledo, OH	610001	10.5	0	10.5	0	6.36	6.36
Topeka, KS	233870	8.18	4.44	12.62	8.18	4.44	12.62
Trenton, NJ	366513	0	0	0	0	0	0
Tucson, AZ	980263	0	0	0	0	0	0
Tulsa, OK	937478	16.75	0	16.75	21.34	19.62	40.96
Tuscaloosa, AL	230162	6.85	0	6.85	6.85	0	6.85
Tyler, TX	209714	0	0	0	0	0	0
Utica-Rome, NY	299397	6.34	0	6.34	0	24.09	24.09
Valdosta, GA	139588	21.75	0	21.75	21.75	0	21.75
Vallejo-Fairfield, CA	413344	0	0	0	0	0	0
Victoria, TX	94003	7.67	19.77	27.44	0	13.1	13.1
Virginia Beach-Norfolk-Newport News, VA-NC	1676822	12.01	0	12.01	12.01	0	12.01
Visalia-Porterville, CA	442179	0	0	0	0	0	0
Waco, TX	252772	7.07	0	7.07	7.07	0	7.07
Walla Walla-Kennewick-Richland, WA*	316199	1.29	0	1.29	1.29	0	1.29
Warner Robins, GA	179605	15.42	0	15.42	15.42	0	15.42
Washington-Arlington-Alexandria, DC-VA-MD-WV	5636232	7.73	0	7.73	7.73	0	7.73
Waterloo-Cedar Falls, IA	167819	21.89	0	21.89	21.89	0	21.89
Watertown-Fort Drum, NY	116229	0	18.9	18.9	0	18.9	18.9
Wausau, WI	134063	0	0	0	0	0	0
Weirton-Steubenville-Wheeling, WV-OH*	272404	0	0	0	0	0	0
Wenatchee, WA	110884	0	0	0	0	0	0
Wichita Falls, TX	151306	13.09	0	13.09	13.09	0	13.09
Wichita, KS	630919	5.07	0	5.07	5.07	0	5.07
Williamsport, PA	116111	0	25.26	25.26	0	25.26	25.26
Wilmington, NC	254884	0	0	0	0	0	0
Winston-Salem, NC	640595	19.83	0	19.83	19.83	0	19.83
Yakima, WA	243231	0	0	0	0	0	0
York-Hanover, PA	434972	0	0	0	0	0	0
Youngstown-Warren-Boardman, OH-PA	565773	0	0	0	0	0	0
Yuba City, CA	166892	0	0	0	0	0	0
Yuma, AZ	195751	0	0	0	0	0	0