National Expenditures on Local Amenities

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We develop a framework for estimating Americans' implicit expenditures on spatially varying nonmarket amenities. We focus on location-specific factors that affect the quality of life but are not formally traded. Examples include climate, geography, pollution, local public goods, and transportation infrastructure. Households pay for residential access to these amenities indirectly, through housing prices, wages and property taxes. We construct a database of 75 amenities, match it to 5 million households' location choices, and use hedonic methods to estimate their total amenity expenditures. Our benchmark estimate for the year 2000 is $562 billion--equivalent to 8% of Americans' personal consumption expenditures.

Keywords: revealed preference; hedonic; nonmarket valuation; local amenities

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The quality of life depends on numerous spatially varying amenities that are not formally traded in private markets, such as the local climate, environmental quality, and local public goods. These amenities influence where people choose to live and work. For instance, the American Housing Survey reports that over 20% of recent movers cite local amenities as the main reason why they moved to their neighborhoods.[1] People pay for these amenities indirectly, through higher housing prices higher property taxes, and lower real wages. These indirect expenditures appear to be substantial. Housing accounts for 18% of all U.S. personal consumption expenditures and hedonic property value studies document that spatial variation in a single amenity can move prices by a percentage point or more. Examples include cancer risk (Davis 2004), air pollution (Chay and Greenstone 2005), and public school test scores (Kuminoff and Pope 2014). If we could add up the amounts that Americans implicitly spend on these and all other local amenities, it is easy to imagine that the total could represent a significant fraction of personal consumption expenditures. However, three factors preclude making this calculation. First, differences across property value studies in terms of geography and time period prevent us from simply adding up existing estimates to get a consistent national total. Second, there is relatively little evidence on wage capitalization of amenities. Third, the set of amenities studied by the existing literature is incomplete.

The purpose of this paper is to develop and implement a methodology for calculating households' implicit expenditures on local amenities. We begin by constructing a database of amenities in U.S. counties. We define "amenities" broadly to include all location-specific characteristics that matter to households but are not formally traded in private markets. This includes features of climate, geography, pollution, public goods, opportunities for dining and entertainment, and transportation

[1] For example, the 2001 American Housing Survey reports that 25% of recent movers listed the main reason for their neighborhood choice as: "looks/design of neighborhood", "good schools", "convenient to leisure activities", "convenient to public transportation", or "other public services." This statistic was 23% when the question was asked again in 2013.

infrastructure. We use the scope of prior studies in the hedonic property value literature to guide our efforts to collect data on these amenities for every county in the lower 48 states for the year 2000. Examples of the 75 amenities in our database include rainfall, humidity, temperature, frequency of extreme weather, wilderness areas, state and national parks, air quality, hazardous waste sites, municipal parks, crime rates, teacher-pupil ratios, child mortality, airports, train stations, restaurants and bars, golf courses, and research universities.[2] We match our amenity data to the 5% public use micro data sample from the 2000 Census, providing data on over 5 million households' housing expenditures, wages, and residential locations.

We develop a revealed preference approach to calculating amenity expenditures. Our approach is based on a simple model of spatial equilibrium in the presence of Tiebout and Roy sorting. Heterogeneous households are assumed to choose where to live and work based, in part, on their idiosyncratic job skills and preferences for amenities. This causes spatial variation in amenities to be capitalized into land values and wages. All else constant, people must pay to live in higher amenity areas through some combination of higher housing prices, higher property taxes, and/or lower real wages. We define "amenity expenditures" as the real income that households choose to forego in order to consume the amenity bundles at their chosen locations.

The expenditure calculations proceed in three stages. First, we calculate real wages and real housing expenditures for each household. Specifically, we adjust gross nominal wages for spatial variation in purchasing power and income tax burdens, and then we calculate real housing expenditures by adjusting for local differences in the user cost of housing due to property taxes and tax subsidies to homeowners, adapting methods developed by Poterba (1992), Himmelberg, Mayer, and

[2] The year 2000 is a natural benchmark because national data on many amenities were first reported in the late 1990s.

Sinai (2005), Albouy (2009), and Moretti (2013). Second, we use hedonic regressions to extract the spatial variation in real wages and rents that is explained by spatial variation in amenities. Finally, we calculate each household's amenity expenditures by combining the rent and wage differentials with data on the physical and financial costs of moving around the United States. Specifically, we measure a household's amenity expenditures as the maximum amount by which it could increase its real income by moving within the contiguous United States to a location with a different amenity bundle, less moving costs, holding fixed the household's labor supply and the type of house it would occupy. This calculation provides a revealed preference measure of the real income that a household chooses to forego in order to enjoy its preferred amenity bundle.

Our econometric strategy for using hedonic regressions to attribute rent and wage differentials to amenities addresses two key identification challenges. First, workers with higher unobserved job skill may choose to live in higher amenity areas. This sorting behavior would make it difficult to distinguish wage capitalization of amenities from wage compensation of human capital. We disentangle these two factors by using migration data to implement Dahl's (2002) selection correction procedure. Intuitively, if there is a low probability that a worker would migrate from her birth region to her observed labor market, then her choice to do so may reveal that she has high person-place specific human capital. Based on this logic, we use data on migration patterns to estimate a residual measure of latent human capital that we control for in the hedonic wage regression.

The second identification challenge is that our amenity database is incomplete. It is unrealistic to expect that any such database could be fully comprehensive. We address omitted amenities by showing that our estimator identifies *total* amenity expenditures if omitted amenities can be expressed as a linear function of the 75 amenities in our database. Two empirical observations suggest that this condition may provide a reasonable approximation. First, amenities exhibit a high degree of spatial correlation. Second, the size and scope of our database makes it likely that any omitted amenity will be highly correlated with several of the ones we observe.

We find that Americans implicitly spent approximately $562 billion on their preferred bundles of local amenities in the year 2000 or $5,365 per household. This is equivalent to 8.2% of all personal consumption expenditures (PCE) on private goods. To put these figures in perspective, the national income and product accounts report expenditures of $1,010 billion on housing (18% of PCE), $918 billion on health care (14%), $231 billion on recreation (3%), and $184 billion on energy (3%). We analyze heterogeneity in expenditures and find that they are generally higher in the west, mountain and northeast regions, and lower in the mid-west and south. Among major metropolitan areas, expenditures per household are highest in San Francisco, New York, and Los Angeles and lowest in Detroit, Baltimore, and Houston. Looking within metropolitan areas, we find that expenditures tend to be higher among people who are older, better educated, and have higher non-wage income. Finally, we note that rents and wages both contribute substantially to our expenditure measures. If we ignore housing price differentials when making expenditure calculations our estimate is still $163 billion (29% of the total). Our estimated ranking of locations by per capita amenity expenditures is very different from typical popular press rankings of "best places to live" because we calculate expenditures using revealed preference methods that avoid making normative judgements about how to weight individual amenities and the cost of living.[3]

Our study builds on the quality of life literature following Rosen (1979) and Roback (1982). Numerous studies have adapted Roback's representative agent model to rank urban areas by the quality of life and to estimate how much people

[3] For example, according to Money Magazine the top 3 "Best Places to Live in the U.S. in 2021-2022" are Chanhassen Minnesota, Carmel Indiana, and Franklin Tennessee. The methodology they used to derive this result involved limiting the set of ranked locations to those with populations less than 500k, assigning relatively large ad hoc weights to crime, population trends, ethnic diversity, cost of living, economic opportunity, and housing affordability, and excluding locations that had been ranked highly the previous year.

would be willing to pay for amenity changes (e.g. Blomquist, Berger, and Hoehn 1988, Gyourko and Tracy 1991, Kahn 1995, Blomquist 2006, Kahn 2006, Bayer, Keohane, and Timmins 2009, Hamilton and Phaneuf 2012, Albouy 2015, 2016, Taylor, Phaneuf and Liu 2016, Albouy, Ehrlich, and Shin 2017, Severen and Plantinga 2018, Sinha, Caulkins and Cropper 2018, Ma 2019, Albouy, Christensen and Sarmiento-Barbieri 2020). We extend this literature in several ways. Most importantly, we provide the first measure of amenity expenditure *levels*. This metric complements and extends prior estimates for expenditure *differentials* and quality of life rankings. Because our expenditure measure defines the share of potential income spent on amenities, it can be compared to private good expenditures. For instance, if we were to define nonmarket amenities as a sector of the economy based on our PCE measure, it would be smaller than health care but larger than the recreation and energy sectors combined. Knowing how much households are implicitly spending on nonmarket amenities would be useful for policymakers at both the local and federal levels when they make decisions that might affect the tradeoff between market and nonmarket amenities.[4] This knowledge also provides data moments that could assist in calibrating economic models used to evaluate federal policies targeting nonmarket amenities (Rogerson 2015, Shimer 2013, Smith 2012).

Further, our econometric approach to calculating amenity expenditures refines standard methods from the quality-of-life literature in three ways. First, we flexibly incorporate spatial variation in the user cost of housing that arises from heterogeneity in income taxes, property taxes, the cost of finance and housing appreciation rates. Second, we illustrate how control functions can be used to mitigate biases

[4] For example, investment decisions at both local and federal levels that may be compliments or substitutes to nonmarket amenities, should optimally take into account the current levels of nonmarket amenity expenditures. Policymakers may also want to evaluate how their programs or policies influence amenity expenditures. Furthermore, changes in the implicit spending on nonmarket amenities over time may provide policymakers with insights on how preferences for nonmarket amenities relative to market amenities are changing over time helping them to make useful predictions about the needs of their constituency.

from spatial sorting on human capital. Finally, we adjust expenditures for the physical and financial costs of moving. Each refinement is quantitatively important for our estimates and can be integrated into future efforts to develop quality of life indices. We demonstrate this by showing how adding amenities and refining our econometric methodology changes the way that major metropolitan counties would be ranked under the Roback (1982) model assumptions.

Our amenity database also represents a major expansion in scale and scope compared to databases compiled by prior studies such as Blomquist, Berger, and Hoehn (1988) who collected data on 15 amenities in 253 urban counties circa 1980, and Albouy (2016) who collected data on 10 amenities in metro and non-metro areas circa 2000. Our new database could provide the basis for developing a formal satellite account of nonmarket amenities in future research and we outline some of the remaining challenges that would have to be met to accomplish this task.

Finally, we highlight three remaining limitations of our framework that provide opportunities for further research. First, our identification strategy is not designed to decompose total amenity expenditures into a vector of implicit expenditures on individual amenities. In principle, our framework could be extended to recover expenditures on particular amenities by using instrumental variables to isolate exogenous variation in them. Second, because our expenditure measures are derived from between-county variation in amenities they obscure the within-county heterogeneity in expenditures across households. Future research could document this latent heterogeneity by repeating our analysis with more spatially granular data. Finally, interpreting our results as revealed preference measures for how much households actively choose to spend on amenities requires that we take a stance on how they perceive their job and housing options. We explore the sensitivity of our estimates to alternative choice set definitions and find that our estimates range from \$385 to \$582 billion under extreme exclusive and inclusive definitions for choice sets. Future research could refine our approach by surveying households about how they perceive their job-house-amenity options.

The rest of the paper proceeds as follows. Section I uses a sorting model to define amenity expenditures. Section II summarizes the data. Section III explains our econometric methodology, Section IV presents the main results, and Section V concludes. Additional modeling details are provided in a supplemental appendix.

I. Conceptual Framework

A. Dual-Market Sorting Equilibrium

We begin from a static framework for modeling spatial sorting behavior, in which heterogeneous firms and households are assumed to choose locations to maximize profits and utility (Roback 1982, Blomquist, Berger, and Hoehn 1988, Bayer, Keohane, and Timmins 2009).[5] We first divide the nation into $j = 1,2, \dots, J$ locations that differ in the wages paid to workers, w_j, in the annualized after-tax price of land, which we call rent, r_j, and in a vector of K nonmarket amenities, $A_j = [a_{1j}, \dots, a_{Kj}]$. We define "amenities" broadly to include all attributes of a location that matter to households but are not formally traded. Examples include climate, geography, pollution, public goods, opportunities for dining and entertainment, and transportation infrastructure. Some of these amenities are exogenous (e.g. climate, geography), whereas others may be influenced by Tiebout sorting through voting on property tax rates, social interactions, and feedback effects (e.g. school quality, pollution).

Heterogeneous households choose locations that maximize utility. They differ in their job skills, preferences for amenities, and in the set of locations to which they would consider moving. Let $J_\alpha \subset J$ denote the subset of locations considered by a household of type α. If we define locations to be counties, for example, then

[5] It is difficult to develop dynamic models of spatial sorting behavior that retain the heterogeneity in preferences and skills thought to underlie sorting equilibria. Kennan and Walker (2011), Bayer et al. (2016) and Mangum (2012) take first steps in this direction.

the typical household may only be familiar with the rents, wages, and amenities in a small subset of the 3000+ counties in the U.S. Likewise, a worker may only find job opportunities in a small subset of counties.

Households enjoy the quality of life provided by the amenities in their chosen locations. Each household supplies one unit of labor, for which it is paid according to its skills. A portion of this income is used to rent land, h, and the remainder is spent on a nationally traded private good, x.[6] Thus, households maximize utility by selecting a location and using their wages to purchase x and h,

$$\text{(1)} \qquad \max_{h,x,j \in J_\alpha} U\left(x, h, A_j; \alpha\right) : \quad w_j(\alpha) = x + r_j h + mc_{\alpha,j}.$$

Households also face differentiated costs of moving to a given location. This is represented by $mc_{\alpha,j}$. Notice that we use α to index all forms of household heterogeneity. Each α-type has a unique combination of preferences, skills, and moving costs, and considers a specific subset of the J locations.

The firm side of the model is analogous. β-type firms with heterogeneous production technologies and management styles choose locations that minimize their cost of producing the numéraire good, $C_j = C\left(w_j, r_j, A_j, mc_{\beta,j}; \beta\right)$.[7]

A dual-market sorting equilibrium occurs when rents, wages, amenities, and location choices are defined such that markets for land, labor, and the numéraire good clear and no agent would be better off by moving. This implies that utility and costs are equalized across all of the locations occupied by households of each α-type and firms of each β-type. Denoting these subsets of occupied locations as J_α^*, J_β^* and rewriting utility in indirect terms, we have:

[6] The composite good includes the physical characteristics of housing. While this aggregation is a standard feature of models following Roback (1982) it embeds a potentially strong assumption that implicit prices of physical housing characteristics do not vary across space. Our empirical model relaxes this assumption by allowing for spatial variation in the user cost of housing and regional variation in the implicit prices of physical house characteristics.

[7] Amenities may affect the cost of doing business. An example would be a firm with a dirty production technology facing stricter environmental regulations if it locates in a county that violates federal standards for air quality. Firms may also face heterogeneous costs of moving physical capital to a given location.

(2.a) $$\bar{V}_\alpha = V\left(w_j, r_j, A_j, mc_{\alpha,j}; \alpha\right) \quad \text{for all} \quad j \in J^*_\alpha.$$

(2.b) $$\bar{C}_\beta = C\left(w_j, r_j, A_j, mc_{\beta,j}; \beta\right) \quad \text{for all } j \in J^*_\beta \ .$$

Under the assumption that each location provides a unique bundle of amenities, we can use hedonic price and wage functions to describe the spatial relationships between rents, wages, and amenities that must be realized in equilibrium:

(3) $$r_j = r\left[A_j; F(A), G(\alpha), H(\beta)\right] \quad \text{and} \quad w_j = w\left[A_j; F(A), G(\alpha), H(\beta)\right],$$

where *F*, *G*, and *H* denote the distributions of amenities, households, and firms. Following standard practice in the empirical sorting literature, we assume that markets are observed in equilibrium and then we focus on estimating equilibrium relationships between rents, wages and amenities (Epple, Gordon, and Sieg 2010, Kuminoff, Smith, and Timmins 2013).[8]

Spatial variation in rents and wages determines the implicit price of consuming amenities. Consider air quality. There are two ways to induce a household to move to a smoggier location: higher wages or lower rents. The extent to which movers are compensated through wages, relative to rents, will depend on the spatial distribution of air quality as well as the extent to which air quality affects the cost of production and the quality of life.

B. Implicit Expenditures on Amenities

We define a household's *amenity expenditures* to be the amount of income it chooses to sacrifice in order to consume the amenities conveyed by its preferred location. To define this concept formally let x^* and h^* represent the household's

[8] If each location has a distinct bundle of amenities, as in our application, it is trivial to prove that the equilibrium relationship between rents and amenities (or wages and amenities) can be described by a hedonic price function, as opposed to a correspondence. Roback (1988), Bayer, Keohane, and Timmins (2009), and Kuminoff (2013) analyze the properties of dual-market sorting equilibria under specific assumptions about household heterogeneity.

consumption at its utility-maximizing location, and let q_α represent amenity expenditures for an α-type household. Then we have,

$$(4) \qquad q_\alpha = \acute{x} - x^*, \quad \text{where} \quad \acute{x} = \max_{l \in J_\alpha} \; w_l(\alpha) - r_l h^* - mc_{\alpha,l}.$$

Thus, q_α is the additional income a household would collect if it were to move from its present, utility maximizing location to the least expensive location in its consideration set and rent a house identical to the one it occupies currently.[9] The least expensive location in J_α defines the household's reference point, $\acute{x}$, used to normalize the expenditure calculation. Different households may have different reference points due to heterogeneity in consideration sets and moving costs.

The revealed preference logic of (4) implies that amenity expenditures must be nonnegative. If a household cannot reduce its expenditures by moving away from its present location then $\acute{x} = x^*$ and $q_\alpha = 0$. Otherwise, $q_\alpha > 0$. Thus, households are effectively endowed with the amenity bundles at the least expensive locations in their consideration sets. This normalization is consistent with the revealed preference logic that discrete choice models use to characterize households' tradeoffs between local amenities and private consumption (e.g. Bayer, Keohane and Timmins 2009, Hamilton and Phaneuf 2015, Sinha, Caulkins and Cropper 2018).

The non-negativity constraint is also consistent with the idea that markets may subsidize households to live in low-amenity areas if, for example, degradation of local amenities causes equilibrium housing prices to fall below their replacement costs. In this case, the price reduction is equivalent to optional income transfer. A

[9] While our definition of amenity expenditures in equation (4) fixes a household's physical house consumption in every counterfactual location to match the house they occupy in their present, utility-maximizing location, our characterization of the utility-maximization problem allows households to choose to adjust their house characteristics when they move. The scope for adjustment is among the reasons why our expenditure measure lacks a precise welfare interpretation, as explained below. In principle, a parametric specification for utility could be added to predict how households would adjust their housing consumption in alternative locations and then calculate associated welfare measures.

household that chooses to forego the opportunity to enjoy more private consumption by moving to the degraded area is implicitly spending more to consume its preferred amenities relative to the degraded bundle. This example reinforces the fact that our expenditure measure is defined by the opportunity to adjust consumption by moving between locations that offer different bundles of housing prices, wages, and amenities. If a hypothetical government policy were to equalize amenities across space, welfare might improve, but individual households would lose their ability to choose how much to spend on amenities.

The discrete nature of the choice set also recognizes that some households may be at corner solutions. For example, households who choose to live in the lowest amenity areas may still prefer to consume more of x in exchange for fewer amenities. In principle this might be achieved by moving to a different country, but it seems reasonable to assume that the cost of international migration is sufficiently high to prevent most households from considering this option.

In addition to providing the logic for our expenditure calculations, equation (4) illustrates how our model relates to prior literature on ranking areas by their quality of life. The connection starts from the observation that $q_\alpha = \acute{x} - x^*$ is simply the revealed preference notion of an income equivalent (Fleurbaey 2009). Income equivalents generally lack a precise welfare interpretation. A welfare interpretation for q_α can be obtained by adding simplifying assumptions from the quality-of-life literature. In particular, (2)-(3) simplify to Roback's (1982) model of compensating differentials if households and firms: (i) consider locating in every jurisdiction: $J_\alpha = J_\beta = J$; (ii) are freely mobile: $mc_{\alpha,j} = mc_{\beta,j} = 0 \;\; \forall \, \alpha, \beta$; and (iii) are homogenous.[10] Under these restrictions, q_α defines the representative agent's Hicksian

[10] To obtain the result from Roback (1982) differentiate indirect utility, $dV = 0 = \frac{\partial V}{\partial w} dw_j + \frac{\partial V}{\partial r} dr_j + \frac{\partial V}{\partial q}\frac{\partial q}{\partial a} da_{kj}$, and apply Roy's identity to obtain $p_{kj} \equiv h_j \left(\frac{dr_j}{da_{kj}}\right) - \frac{dw_j}{da_{kj}} = \left(\frac{\partial V}{\partial q}\frac{\partial q}{\partial a}\right) / \frac{\partial V}{\partial w}$. The implicit price of an amenity, p_{kj}, is defined by the rent differential times land rented, minus the wage differential. The second equality indicates that the equilibrium value for p_{kj} reveals the representative agent's willingness to pay for one unit of the amenity.

willingness to pay for the associated amenity bundle and demand curves for amenities are identified by the equilibrium hedonic price and wage equations. This interpretation underlies the literature on ranking cities by a universal measure for the quality of life (e.g. Blomquist, Berger, and Hoehn 1988, Gyourko and Tracy 1991, Kahn 2006, Blomquist 2006, Albouy 2016).

While the additional Roback (1982) assumptions usefully connect our model to prior literature and can provide a basis for ranking areas according to the quality of life, they are not required to calculate amenity expenditures. Equation (4) shows that we can use revealed preference logic to measure households' amenity expenditures even if they face heterogeneous moving costs and differ in how they would rank areas according to the quality of life.

II. Data

We collected data on 75 amenities in each of the 3,108 counties comprising the contiguous United States.[11] Using information on house location, we matched these amenities to public use microdata records from the 2000 Census of Population and Housing. The closest comparison to these data in the prior literature are to Blomquist, Berger, and Hoehn (1988) who assembled data on 15 amenities for 253 urban counties circa 1980 and Albouy (2016) who assembled data on 10 amenities for metro areas circa 2000. As in their studies and much of the broader quality of life literature we focus on place-based amenities that may affect household utility. We chose these amenities based on a literature review that we summarize in section A below. We then collected information on all of the amenities that were available consistently across counties in the U.S. Specifically, we characterize each location's climate and geography, environmental externalities, local public goods,

[11] Unfortunately, we were unable to obtain data on several amenities in Alaska and Hawaii. We chose to omit these states, rather than the amenities. Omitting Alaska and Hawaii is unlikely to have a significant impact on our approximations to national amenity expenditures because, in 2000, the two states jointly accounted for less than 0.75% of GDP.

transportation infrastructure, and access to cultural and urban amenities that may include opportunities for social interaction. In contrast to some previous work, our database excludes amenities that are purely productive (e.g. tax advantages offered to firms).

A. Amenities

Table 1 reports summary statistics for the amenities we collected. As a baseline for comparison, we also report means for the subset collected by Blomquist, Berger, and Hoehn (1998) [henceforth BBH] which also includes most of the amenities tracked by Albouy (2016). Column (1) reports 1980 means for the BBH amenities. Column (2) reports year 2000 means for our full set of amenities in the 253 urban counties studied by BBH. Finally, column (3) reports year 2000 means for our full set of amenities in all 3,108 counties.[12]

Table 1: Amenity Summary Statistics

	1980	2000		
	BBH	BBH	Nation	
	Mean	*Mean*	*Mean*	*Sources**
	(1)	(2)	(3)	(4)
GEOGRAPHY AND CLIMATE				
Mean precipitation (inches p.a., 1971-2000)	32.00	38.22	38.64	NOAA-NCDC
Mean relative annual humidity (%, 1961-1990)	68.30	67.76	67.25	NOAA-NCDC
Mean annual heating degree days	4,326	4,632	4,914	NOAA-NCDC
Mean annual cooling degree days	1,162	1,295	1,300	NOAA-NCDC
Mean wind speed (m.p.h., 1961--1990)	8.89	8.91	9.13	NOAA-NCDC
Sunshine (% of possible)	61.10	59.51	60.21	NOAA-NCDC
Heavy fog (no. of days with visibility ≤ 0.25 mi.)	15.80 †	20.30	21.42	NOAA-NCDC
Percent water area	--	9.99	4.59	ICPSR
Coast (=1 if on coast)	0.33	0.29	0.10	NOAA-SEAD
Non-adjacent coastal watershed (=1 if in watershed)	--	0.21	0.11	NOAA-SEAD
Mountain peaks above 1,500 meters	--	7.10	7.40	ESRI
Rivers (miles per sq. mile)	--	0.24	0.20	USDI-NPS
Federal land (percentage of total land area)	--	9.17	12.58	USGS-NA
Wilderness areas (percentage of total land area)	--	1.14	0.87	USGS-NA
National Parks (percentage of total land area)	--	0.80	0.53	USGS-NA
Distance (km) to nearest National Park	--	71.81	97.19	USDI-NPS
Distance (km) to nearest State Park	--	22.68	32.81	USDI-NPS
Scenic drives (total mileage)	--	0.21	0.16	USGS-NA

[12] Variables that were measured at a finer level of spatial resolution than a county were aggregated to the county level. For some of the geographic and environmental variables, we use irregularly-spaced NOAA and EPA source data from which we then produce county-level data. In these cases, we spatially interpolated the amenity data to the population-weighted county centroids via universal kriging. Universal kriging produces superior results to simpler techniques such as inverse distance weighting because it permits the spatial variogram to assume functional forms that include directional dependence.

Average number of tornados per annum (1950-2004)	--	0.44	0.27	USGS-NA
Property damage from hazard events ($000s, per sq. mile)	--	59.75	31.17	USGS-NA
Seismic hazard (index)	--	2,029	1,984	USGS-NA
Number of earthquakes (1950-2000)	--	3.47	0.93	USGS-NA
Land cover diversity (index, range 0-255)	--	146.37	121.62	USGS-NA
ENVIRONMENTAL EXTERNALITIES				
NPDES effluent dischargers (PCS permits, 1989-1999)	1.51	17.52	4.29	EPA-TRI
Landfill waste (metric tons, 2000)	4,770	4,112	1,300	EPA-TRI
Superfund sites	0.88	2.73	0.52	EPA-TRI
Treatment, storage and disposal facilities	46.40	34.74	5.19	EPA-TRI
Large quantity generators of hazardous waste	--	221.83	33.42	EPA-TRI
Nuclear power plants	--	0.06	0.02	USDOE-INSC
PM2.5 (μg per m^3)	--	13.51	12.83	EPA-AQS
PM10 (μg per m^3)	73.20 ‡	23.61	23.21	EPA-AQS
Ozone (μg per m^3)	--	10.07	9.34	EPA-AQS
Sulfur dioxide (μg per m^3)	--	1.49	1.36	EPA-AQS
Carbon monoxide (μg per m^3)	--	5.95	8.59	EPA-AQS
Nitrogen dioxide (μg per m^3)	--	5.66	4.37	EPA-AQS
National Fire Plan treatment (percentage of total area)	--	0.11	0.14	USGS-NA
Cancer risk (out of 1 million equally exposed people)	--	4.14	1.80	EPA-NATA
Neurological risk	--	0.10	0.06	EPA-NATA
Respiratory risk	--	5.41	1.98	EPA-NATA
LOCAL PUBLIC GOODS				
Local direct general expenditures ($ per capita)	--	3.44	2.93	COG97
Local exp. for hospitals and health ($ per capita)	--	47.05	564.60	COG97
Local exp. on parks, rec. and nat. resources ($ pc)	--	15.83	126.71	COG97
Museums and historical sites (per 1,000 people)	--	8.53	1.73	CBP
Municipal parks (percentage of total land area)	--	1.54	0.25	ESRI
Campgrounds and camps	--	6.42	2.30	CBP
Zoos, botanical gardens and nature parks	--	1.82	0.36	CBP
Crime rate (per 100,000 persons)	647	4,784	2,653	ICPSR
Teacher-pupil ratio	0.080	0.092	0.107	COG97
Local expenditure per student ($, 1996-97 fiscal year)	--	37.05	19.51	COG97
Private school to public school enrollment (%)	--	23.54	13.13	2000 Census
Child mortality (per 1000 births, 1990--2000)	--	7.31	7.52	CDC-NCHS
INFRASTRUCTURE				
Federal expenditure ($ pc, non-wage, non-defense)	--	5,169	4,997	COG97
Number of airports	--	2.13	1.23	USGS-NA
Number of ports	--	0.27	0.05	USGS-NA
Interstate highways (total mileage per sq. mile)	--	0.09	0.03	USGS-NA
Urban arterial (total mileage per sq. mile)	--	0.26	0.05	USGS-NA
Number of Amtrak stations	--	1.19	0.25	USGS-NA
Number of urban rail stops	--	7.50	0.81	USGS-NA
Railways (total mileage per sq. mile)	--	0.48	0.27	USGS-NA
CULTURAL AND URBAN AMENITIES				
Number of restaurants and bars (per 1,000 people)	--	0.92	1.01	CBP
Theatres and musicals (per 1,000 people)	--	0.02	0.01	CBP
Artists (per 1,000 people)	--	0.18	0.11	CBP
Movie theatres (per 1,000 people)	--	0.02	0.02	CBP
Bowling alleys (per 1,000 people)	--	0.02	0.03	CBP
Amusement, recreation establishments (per 1,000 people)	--	0.42	0.32	CBP
Research I universities (Carnegie classification)	--	0.24	0.03	CCIHE
Golf courses and country clubs	--	16.15	3.79	CBP
Military areas (percentage of total land area)	--	1.18	0.83	USGS-NA
Housing stress (=1 if > 30% of households distressed)	--	0.37	0.16	USDA-ERS
Persistent poverty (=1 if > 20% of pop. in poverty)	--	0.03	0.12	USDA-ERS
Retirement destination (=1 if growth retirees > 15%)	--	0.07	0.14	USDA-ERS
Distance (km) to the nearest urban center	--	10.98	33.59	PRAO-JIE09

Incr. distance to a metropolitan area of any size	--	0.20	35.80	PRAO-JIE09
Incr. distance to a metro area > 250,000	--	23.11	54.90	PRAO-JIE09
Incr. distance to a metro area > 500,000	--	32.09	39.36	PRAO-JIE09
Incr. distance to a metro area > 1.5 million	--	76.45	86.79	PRAO-JIE09

Notes: The amenity data were constructed from the following sources: CCIHE: Carnegie Classification of Institutions of Higher Education; CBP: 2000 County Business Patterns published by the Census Bureau; CDC-NCHS: Centers for Disease Control and Prevention, National Center for Health Statistics; COG97: 1997 Census of Governments; EPA-AQS: 2000 data for criteria air pollutants from the Air Quality System produced by the Environmental Protection Agency (EPA); EPA-NATA: 1999 National-Scale Air Toxics Assessment conducted by the EPA; EPA-TRI: 2000 Toxic Release Inventory published by the EPA; ESRI: Environmental Systems Research Institute ArcGIS maps; ICPSR: U.S. County characteristics complied by the Inter-university Consortium for Political and Social Research ICPSR2008; NOAA-SEAD: Strategic Environmental Assessments Division of the National Oceanic and Atmospheric Administration; NOAA-NCDC: National Climatic Data Center of the National Oceanic and Atmospheric Administration; PRAO-JIE09: Partridege et al. (2009); USDA-ERS: Economic Research Service of the US Department of Agriculture; USDI-NPS: National Park Service of the US Department of the Interior; USDOE-EERE: Energy Efficiency and Renewable Energy, US Department of Energy; USDOE-INSC: International Nuclear Safety Center at the US Department of Energy; USGS-NA: National Atlas of the US Geological Survey. † The unit in the BBH visibility variable is miles, rather than total days with a minimum visibility of less than 0.25 miles. ‡ BBH use data on total suspended particulates (TSP), a precursor measure to PM10.

Most of the BBH amenities were fairly constant between 1980 and 2000. In cases where we do see large changes, they appear to be due to changes in the way a variable is measured and reported, or refinements on our part. For example, we refine the definition of a "coastal" county to distinguish between counties that are physically adjacent to the coast and counties that are part of a coastal watershed, but not physically adjacent. Similarly, in the case of particulate matter (PM), we replaced total suspended particulates with measures of $PM_{2.5}$ and PM_{10} to reflect changes in the way the Environmental Protection Agency (EPA) monitors air pollution. The two largest changes are an increase in the number of Superfund sites per county (from 0.88 to 2.73) and an increase in entities requiring water pollution permits (from 1.51 to 16.67). Both increases reflect expansions of EPA's regulatory programs in the 1980s and 1990s.[13]

The amenities that BBH collected emphasize climate, geography, and environmental externalities. Other important amenities were excluded due to limits on data availability at the time of their study. We collected these additional amenities with

[13] In the late 1980s, large increases in the Superfund budget allowed more sites to be added. Likewise, the NPDES permitting system was expanded to regulate entities that only discharge pollution during storms.

help from the sources cited in column (4). New geographic amenities include mountains, rivers, proximity to state and national parks, and measures of the frequency, intensity, and damages of hazardous events such as tornadoes, earthquakes, wild fires, floods, and hurricanes. Earthquakes, for example, have been found to be important for property values in California (Brookshire et al. 1985) and the risk of damage from hurricanes is important in the Gulf Coast and South Atlantic regions (Strobl 2011). We have also added several externalities that are known to affect property values and migration patterns, such as cancer risk (Davis 2004), and the proximity to noxious facilities like large quantity generators of hazardous waste or nuclear power plants (Clark and Nieves 1994).

Gyourko and Tracy (1991) suggest that local public goods are just as important as geography and the natural environment in determining the quality of life. Motivated by their analysis, we assembled data on numerous public goods. Examples include crime rates, the teacher-pupil ratio, child mortality, and municipal parks and museums. Some of these output measures seem too crude to reflect the quality of the underlying amenity. As a proxy for quality, we added selected input measures such as per capita expenditures on health, education, and parks.[14]

A household's location also defines their opportunities for consuming private goods and entertainment. The idea that the diversity of consumption opportunities enhances the quality of life is important to urban economic models of the "consumer city", both as a driver of growth and in determining the wage structure (Glaeser et al. 2001, Lee 2010). Therefore, we developed several measures of the concentration of cultural and urban amenities (e.g. major research universities, theatres, restaurants and bars, golf courses and country clubs).[15] As an additional proxy, we

[14] Brueckner and Neumark (2014) provide additional motivation for including these variables by demonstrating that there is a robust link between public-sector wage differentials and local amenities.

[15] It may seem odd to treat occupation as an amenity in the case of the number of artists per 1000 people. We chose this measure as a proxy for access to the arts (e.g. art galleries, art festivals, art workshops). Likewise, we use the retirement destination indicator as a proxy for access to retirement community amenities and the housing stress and persistent poverty indicators as proxy measures for unobserved features of crime, school quality, and pollution.

measure the distance from each county to the nearest small (less than 0.25 million), medium (0.25m to 0.5m), large (0.5m to 1.5m), and really large (greater than 1.5m) metropolitan area. These measures will help to distinguish non-metro counties that are just outside a major metro area, but close enough to enjoy its amenities, from counties that are located far from metro areas.

Finally, transportation infrastructure may also influence the quality of life. The importance of congestion is well documented. Other influences may be more subtle. For example, Burchfield et al. (2006) find that metro areas with less public transportation tend to have more sprawl and Baum-Snow (2007) demonstrates that interstate highways led to a significant increase in sprawl. To help control for these effects, we measured the mileage of interstate highways and urban arterials per square mile. We also collected data on the concentration of railways, train stations, shipping ports, and airports as proxies for commuting opportunities and the ease of travel.[16]

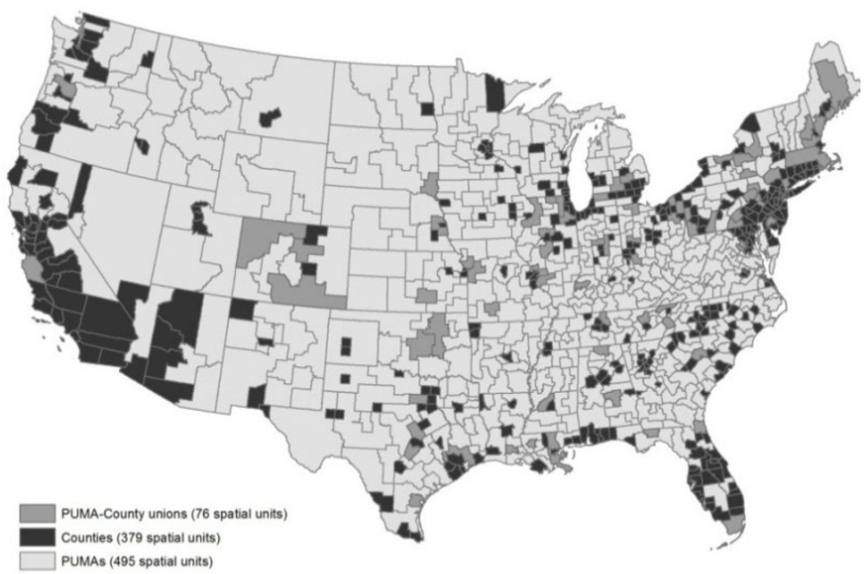
In addition to describing the amenities contained within each county, the database is designed to capture spatial spillovers. In particular, we include several measures of distance to amenities that may be located outside a county (e.g. nearest state park, nearest national park, nearest urban center, nearest metro area). Equally important are the various measures of distance to nearby metro areas, which reflect access to regional markets outside the county. Accounting for these spillover effects is especially important for our study because, unlike most of the quality-of-life literature, we include suburban and rural counties located outside major metropolitan areas.

B. Geography

[16] These features of transportation infrastructure implicitly define the set of commuting options that will influence workers' choices among commuting modes and determine their resulting commute times. Thus, our expenditure measures indirectly reflects commute times without explicitly tracking this endogenous choice variable.

We obtained data on 5.2 million households containing 10.2 million workers from the 5% public-use microdata sample (PUMS) of the 2000 Census.[17] Their residential locations are identified at the level of a "public use microdata area" or PUMA. Because each PUMA must have a population of at least 100,000, PUMA size varies inversely with density. Most metropolitan counties are subdivided into several PUMAs. In contrast, a single PUMA can span several rural counties.[18]

Figure 1: Geography Used to Match Rents, Wages, and Amenities



Note: The figure depicts the 950 locations that we use to calculate amenity expenditures. Every location is a direct aggregation of U.S. counties. There are 379 individual counties containing multiple PUMAs; 495 individual PUMAs containing multiple counties; and 76 county clusters containing PUMAs that overlap county borders.

We merged PUMS data with the amenities in table 1 at the highest possible spatial resolution. This resulted in aggregating the 3,108 counties in the contiguous U.S. into 950 locations shown in figure 1. Of these 950 locations, 379 are metropolitan counties. They cover 60% of the U.S. population. In rural areas where one

[17] Table A3 summarizes how the geography of our study area relates to prior studies.

[18] The most densely populated county (New York County, NY) has 66,951 people per square mile and is covered by ten PUMAs. At the opposite extreme, Loving County, TX—which is the least populous *and* the least densely populated county in the US—has only 0.09 people per square mile; its corresponding PUMA covers fourteen counties.

PUMA covers multiple counties we aggregate amenities to the PUMA level using county population weights.[19] The resulting 495 PUMAs contain 25% of the population. We believe this aggregation is a reasonable approximation. Because the affected counties are rural, residents are more likely to have to cross county lines within the PUMA to access public goods, infrastructure, and cultural amenities. Finally, PUMAs occasionally overlap county borders without encompassing both counties. In these cases, we merged the adjacent counties. There are 76 such PUMA-county unions, representing 15% of the population. Thus, each of the 950 locations is a county or the union of adjacent counties. Our estimation procedures treat each location as offering a distinct bundle of amenities.

C. Calculating Real Wages and Real Housing Expenditures

We use the PUMS data as a starting point for deriving real wages and real housing expenditures. Our derivations adjust the raw Census data on nominal wages and self-reported housing values to control for spatial variation in the tax code and purchasing power. Specifically, we follow Gyourko and Tracy (1991), Albouy (2009), and Moretti (2013) in adjusting gross wages for state and federal income tax rates and for the cost of living (excluding housing).[20]

To calculate real housing expenditures we adapt the user cost methodology (Poterba 1992, Himmelberg, Mayer, and Sinai 2005). Given that the homeownership rate was 67.5% in 2000, translating homeowners' self-assessed housing values into a measure of annualized expenditures is an important step in our analysis. It requires controlling for the tax benefits of homeownership. In 2003, some 40 million households claimed an average of $9,500 in mortgage interest deductions and almost $3,000 in property tax deductions. This renders the homeownership subsidy

[19] Population-weighted amenities can be thought of as the average amenities experienced by residents in a given PUMA (as opposed to applying area-weights which would yield average amenities associated with parcels of land inside a PUMA).
[20] Our calculations are documented in the supplemental appendix.

as one of the most prominent features of the American tax code. Moreover, the spatial incidence of benefits is uneven. Gyourko and Sinai (2003) place the average annual benefits for owner-occupied households at $917 in South Dakota compared to $8,092 in California.

Spatial variation in the homeownership subsidy and property tax rates affects the appropriate discount rate by which housing values are converted into rents. This important point has been overlooked by previous studies. For example, BBH used a constant rate of 7.86% based on simulations by Peiser and Smith (1985) for an ownership interval from 1987-90 under a scenario of anticipated rising inflation. Subsequent studies adopted the same constant rate of 7.86% (Gyourko and Tracy, 1991, Gabriel and Rosenthal 2004, Chen and Rosenthal 2008, Albouy 2016). If regional variation in the homeownership subsidy and property taxes is not trivial, then incorrectly assuming a uniform discount rate will tend to overstate (understate) expenditures in areas with below (above) average housing costs.

To translate housing values into a spatially explicit measure of rents, we define an individual's annual cost of home ownership $\tilde{r}_{ij}$ in location j as

$$\tilde{r}_{ij} = P_{ij}\left[rf + \omega_j - \tau_{ij}\left(rm + \omega_j\right) + \delta - \gamma_{t+1} + \varepsilon_j\right], \tag{5}$$

where P_{ij} is the self-reported property value; rf is the risk free rate (10-year average of 3-month T-bill rates); rm is the mortgage rate (10-year average of 30-year fixed rate mortgage); ω_j is the property tax rate (including state and local taxes); τ_{ij} is the marginal income tax rate; δ is the depreciation rate; γ_{t+1} is the expected capital gain; and ε_j is the owner's risk premium. Thus, imputed rents can be derived as $\tilde{r}_{ij} = P_{ij}\phi_{ij}$, where ϕ_{ij} represents the user cost of housing.

The third term in brackets, $\tau_{ij}\left(rm + \omega_j\right)$, represents the subsidy to homeowners due to the deductibility of mortgage interest payments and property taxes.[21] We

[21] Since Himmelberg, Mayer, and Sinai (2005) report that less than half of tax-filing homeowners actually itemize, we reduce

impute ω_j from reported property tax payments and house values. It has a mean of 1.54% in our national sample.[22] For τ_{ij}, we use average effective marginal income tax rates for 1999 which we collect from the NBER TAXSIM model.[23] For ε_j, we use metro-level housing risk premia from Campbell, Davis, Gallin, and Martin (2009) which helps account for local variation in house price appreciation.[24] Finally, using the estimates from Himmelberg, Mayer and, Sinai (2005) and from Harding, Rosenthal, and Sirmans (2007), we set $rf = 0.045$, $rm = 0.055$, $\delta = 0.025$, and $\gamma_{t+1} = 0.038$ (long-run inflation of 2% plus real appreciation of 1.8%). Our estimates suggest a national average user cost of 5.12%, with a range from 4.16% to 9.89%. This implies a range of values for the price-to-rent ratio of 24.0 to 10.1, with an average of 19.5.[25] The user cost of housing varies greatly across metro areas, and there are also significant within-metro differences as can be seen from Appendix Figure A1.

III. Approximating Amenity Expenditures

A. Econometric Model

We use our measures for real wages, real housing expenditures, and amenities in each of the $l = 1,2,\ldots,950$ locations to approximate the measure of implicit amenity expenditures defined in equation (4). Equation (6) shows how hedonic rent and wage regressions enter the approximation.

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the tax subsidy in our calculations by one half. But even without itemizing, all homeowners receive some tax subsidy as imputed rents do not have to be reported as taxable income.

[22] Summary statistics are reported in appendix table A2.

[23] The TAXSIM model integrates federal and state tax codes, but excludes wage and income taxes imposed at the city level. The Tax Foundation reports that approximately 7% of Americans are subject to these taxes, which are present in some large cities such as New York and Philadelphia. Not accounting for this could cause us to understate amenity expenditures in those areas. It would be useful in future research to develop a national database of city level taxes that could be matched to Census PUMA data.

[24] While we assume that expected capital gains (γ_{t+1}) are constant across location due to well-known data limitations, we are able to capture at least some local variation in expected house price appreciation via the owner's risk premia.

[25] In comparison, the fixed 7.86% figure used in BBH and subsequent studies would imply a price-to-rent ratio of 12.7. Focusing our user cost estimates more narrowly on the 253 urban counties studied by BBH has very little impact on the results. The average user cost increases marginally to 5.16%.

$$q_\alpha = \overbrace{\textstyle\sum_{k=1}^{K} a_{kj}\left[\frac{d\tilde{r}_j}{da_{kj}}\left(Y_{ij}^r, A_j, \beta\right) - \frac{dw_j}{da_{kj}}\left(Y_{mj}^w, A_j, \gamma\right)\right]}^{\textit{relative expenditures in location } j} - \underbrace{\min_{l\in J_\alpha}\left\{\textstyle\sum_{k=1}^{K} a_{kl}\left[\frac{d\tilde{r}_l}{da_{kl}}\left(Y_{il}^r, A_l, \beta\right) - \frac{dw_l}{da_{kl}}\left(Y_{ml}^w, A_l, \gamma\right)\right]}_{\textit{minimum feasible expenditures}} - \underbrace{mc_{\alpha,l}}_{\textit{moving cost}}\right\}. \tag{6}$$

The first term is a measure of amenity expenditures for an α-type household in location *j*. It sums the products defined by multiplying the level of each location *j* amenity by its marginal implicit prices estimated from hedonic rent and wage regressions. Summing these terms recovers the expenditure measure that prior studies have used to rank urban areas by the quality of life, starting with Roback (1982) and Blomquist, Berger and Hoehn (1988). We refer to this statistic as measuring *relative* expenditures because it describes cumulative differences between locations in terms of the hedonic rent and wage functions, but its level is arbitrarily defined by the scaling of covariates in those functions. This arbitrary scaling explains why prior studies' estimates for relative expenditures are negative in many areas.

The second term in equation (6) adds the normalizations needed to define a revealed preference measure of amenity expenditure *levels*. It subtracts the smallest measure of relative expenditures from the household's feasible set of locations after adjusting for the costs of moving to those locations. Thus, equation (6) defines the potential income that a household foregoes in order to consume area *j*'s amenity bundle instead of moving to the location where it would maximize its real income, holding fixed its labor force participation and physical housing characteristics.

In the hedonic rent and wage functions, β and γ are parameter vectors describing the shapes of the empirical analogs to the equilibrium equations in (3), and $\{Y_{ij}^r, Y_{mj}^w\}$ are Census PUMS variables describing the physical characteristics of $i = 1, \dots, I$ houses and the demographic characteristics of $m = 1, \dots, M$ workers who live in location j.[26]

We estimate β and γ in two stages. First we regress rents and wages on the Census PUMS variables, adding fixed effects for locations to each regression. Then we regress the estimated fixed effects on amenities. Our main specification of the first-stage model is based on a semi-log parameterization,

(7.a) *rent function*: $\ln \tilde{r}_{ij} = Y_{ij}^{r}\beta_1 + \lambda_j^r + \varepsilon_{ij}$

(7.b) *wage function*: $\ln w_{mj} = Y_{mj}^{w}\gamma_1 + \lambda_j^w + \nu_{mj}$,

where $\tilde{r}_{ij}$ denotes household i's annual expenditures on housing, w_{mj} denotes worker m's annual wages, λ_j^r, λ_j^w are the location fixed effects, and $\varepsilon_{ij}, \nu_{mj}$ are error terms that include unobserved attributes of houses and workers.[27]

After removing the variation in $\ln \tilde{r}_{ij}$ and $\ln w_{mj}$ that can be explained by the observable attributes of houses and workers, any remaining variation across counties will be absorbed by the location fixed effects: $\hat{\lambda}_j^r$, and $\hat{\lambda}_j^w$. However, the fixed effects will conflate the implicit prices for amenities with the implicit prices for latent attributes of houses and workers. We extract the variation in the fixed effects explained by localized amenities by estimating:

(8) $\hat{\lambda}_j^r = A_j\beta_2 + \alpha^r + \xi_j^r$ and $\hat{\lambda}_j^w = A_j\gamma_2 + \alpha^w + \xi_j^w$.

The resulting estimates for β_2 and γ_2 are then used to calculate relative expenditures in each location.[28]

[26] Control variables in the rent regression include: rooms, bedrooms, size of building, age of building, acreage, type of unit, condominium status, and quality of kitchen and plumbing facilities. The model also includes interactions between all variables and an indicator for renter status. In the wage regression the control variables include: experience measured as age-schooling-6, experience^2, gender*experience, gender*experience^2, marital status, race, gender*marital status, age, children under 18, educational attainment, educational enrollment, citizen status, employment disability, NAICS-based industry class, NAICS-based occupation class, and military status. In both the rent and wage regressions, all variables are also interacted with indicators for Census divisions. This flexibility helps to control for spatial variation in construction costs and labor demand.

[27] Equation (7.b) recognizes that a worker may or may not work in their home county. The maintained assumption is that two workers with identical skills, experiences, and demographics who live in the same county will also earn the same wage.

[28] Since the dependent variables in the first stage of our model are measured in natural logs we must use the Halvorsen-Palmquist adjustment to correct the dependent variables prior to second stage estimation and convert the "percentage" coefficients into dollar values.

It is important to emphasize that our second stage regression mitigates confounding by omitted attributes of workers and houses. In the quality of life literature it is common to rank metro areas by a weighted average of the location fixed effects $(\hat{\lambda}_j^r, \hat{\lambda}_j^w)$ estimated in our first stage regression. However, this approach conflates the price and wage effects of amenities with the price and wage effects of omitted attributes of workers and houses. Our second stage regression reduces the scope for bias by purging worker and house attributes that are uncorrelated with amenities. To assess the practical implications of this point we compared our ranking of locations by expenditures to an alternate one where expenditures are calculated from the first-stage fixed effects (subsuming omitted attributes of workers and houses). The Spearman correlation was 0.83—far enough from 1 for our approach to provide a large improvement in accuracy.

While the regression in (8) purges omitted variables that are *uncorrelated* with amenities, a remaining concern is that some omitted attributes of workers and houses could be spatially correlated with amenities across the 950 locations, biasing our estimates for β_2 and γ_2. In the labor market, this presents a spatial version of the Roy sorting problem that is commonly found to bias wage regressions (e.g. Hwang, Reed, and Hubbard 1992; Dahl 2002; Bayer, Kahn, and Timmins 2011). Specifically, if workers with higher unobserved job skill tend to live in higher amenity areas, then γ_2 will conflate the negative effects of amenities on wages with the positive effects of latent human capital, biasing our expenditure measure toward zero.

We address sorting on unobserved job skill by following Dahl's (2002) approach to using migration data to develop control functions for the first stage wage regression (7.b). One of Dahl's key insights is that a semiparametric sample selection correction for a spatial wage equation can be developed from migration probabilities. Intuitively, if there is a low probability that a worker with a particular set of observed demographic characteristics would migrate from her birth region to the labor market where she currently works, then her migration decision may reflect high unobserverd location-specific human capital. To control for this, we follow Dahl in extending the set of control variables in the wage regression, Y_{mj}^{w}, to include second order polynomial functions of worker-specific migration probabilities. As in Dahl (2002), we calculate probabilites by assigning workers to thirty bins, based on their demographics: five levels of education {less than high school, high school, some college, college graduate, advanced degree} by marriage {0,1} by the age range of their children {all under 6 years, at least one between 6 and 18, none under 18}. Then we use information on each migrant's birth state and current location to determine the probability of that migration choice conditional on demographics. For workers who stay in their birth state, we use both the retention probability and the probability for their first-best alternative location. This control function approach allows spatial sorting by unobserved skill to vary systematically across workers. Section IV shows that this is quantitatively important for our expenditure measures and that our results are robust to using an alternative correction procedure developed by Bayer, Khan, and Timmins (2011).

A related concern is that amenities may be spatially correlated with physical housing characteristics that are not available in the Census data (e.g. marble bathrooms, wood flooring). To investigate the potential for this to bias our results, we repeat the estimation of (7a)-(8) using a more parsimonious set of controls for physical housing characteristics, Y_{ij}^{r}, that excludes Census measures for the quality of kitchen and plumbing facilities. All else constant, these proxy measures for overall housing quality are predicted to increase the prices of owner-occupied houses by 6.3% (kitchen) and 8.5% (plumbing) in our baseline version of (7.a). Excluding them from the regression could therefore increase our measures of amenity expenditures if amenities are positively correlated with physical housing quality across the 950 locations. While our expenditure measures do increase, the size of the change is inconsequential—less than 0.05%. This increases our confidence in the assumption that our expenditure measures are unlikely to be biased by excluding other physical characteristics of houses.

B. Identification

It would be nice to separately identify the virtual price of every amenity as an intermediate step toward calculating total amenity expenditures. However, it is not feasible to do so. We expect the localized amenities that we observe to be correlated with other unobserved amenities. Indeed, observed and unobserved amenities may be jointly determined through voting, social interaction, and environmental feedback effects. For example, nice unobserved amenities may attract larger populations and increase local air pollution. Likewise, people may like to live in neighborhoods with less crime and better schools, in part, because they provide more opportunities for social interaction with better educated households. This would present a seemingly intractable version of the standard omitted variable problem.[29]

Fortunately, we *can* approximate total expenditures on the bundle of observed and unobserved amenities that are capitalized into prices and wages if our amenity database is sufficiently comprehensive that the spatial variation in the amenities that we have omitted (including opportunities for social interaction) can be explained by a linear function of the 75 amenities that we have collected**.** Intuitively, this means that a counterfactual regression of a composite index of unobserved amenities on the vector of observed amenities would have high predictive accuracy. A sufficient condition to obtain high predictive accuracy is that each unobserved amenity can be expressed as a precise linear function of observed amenities. For

[29] There is a vast literature on estimating virtual prices for amenities. Recent studies have made progress in developing research designs that mitigate omitted variable bias and other sources of confounding in the identification of virtual prices for individual amenities (for a review see Kuminoff, Smith, and Timmins 2013). However, no study has developed a research design for the contiguous United States. This makes it highly improbable that one could develop a national research design for 75 separate amenities at the same time.

example, if we could observe location-specific public school quality as households perceive it and regress that latent measure on the observed crime rate, teacher-pupil ratio, local expenditures per student, public-to-private school enrollment ratio, air quality, cooling degree days, number of Research I universities nearby and the 68 other amenities in our database, then the residual variation in latent school quality that could, in principle, be separately capitalized into housing prices and wages would be minimal, limiting the scope for omitted school quality to bias our estimator for total expenditures. Similarly, the "style" of urban amenities, from architectural beauty to the destination experience of local dining services, is likely to be largely explained by observed amenities, such as transportation infrastructure and the density of establishments. This argument is analogous to a rationale that Pakes (2003) uses to argue that hedonic price indices are relatively well suited to dealing with products that are not observed in the market every period.

To formalize this reasoning, consider one additional amenity, z_j. The ideal approximation to expenditures is

(9) $$Q = A(\hat{\beta}_2 - \hat{\gamma}_2) + z(\hat{\kappa}^r - \hat{\kappa}^w)\ ,$$

where $\hat{\beta}_2$ and $\hat{\gamma}_2$ represent selection-corrected estimators for the parameters from equation (8) derived using data for all amenities other than z_j, and $\hat{\kappa}^r$ and $\hat{\kappa}^w$ are consistent estimates for the rent and wage differentials arising from spatial variation in z_j. If we could observe z_j then we could estimate $\hat{\kappa}^r$ and $\hat{\kappa}^w$ and use the results to directly evaluate equation (9). However, if z_j is omitted from the econometric model then the second-stage equation for rents takes the following form:

(10) $$\hat{\lambda}_j^r = A_j\beta_2 + \alpha^r + \xi_j^r, \quad \text{where} \quad \xi_j^r = z_j\kappa^r + \epsilon_j \quad \text{and} \quad E\left[\epsilon_j \middle| A_j, z_j\right] = 0.$$

The probability limit of our estimator for β_2 is now

(11) $$\text{plim}\ \hat{\beta}_2 = \beta_2 + \pi\kappa^r, \quad \text{where} \quad z = A'\pi + \eta \quad \text{and} \quad E\left[\eta_j \middle| A_j\right] = 0.$$

Since $\hat{\gamma}_2$ is defined analagously, our estimator for total expenditures can be written as

$$\text{plim } \hat{Q} = A(\beta_2 - \gamma_2) + (z - \eta)(\kappa^r - \kappa^w) \tag{12}$$

after some substitution.

Equations (11)-(12) formalize the intuition for our approach to identification. There are two key points. First, notice that (11) provides a consistent estimator for the implicit prices of each observed amenity as $\pi \to 0$. Yet, the estimator for total expenditures in (12) is inconsistent. If $\pi = 0$, then $\eta = z$, and plim $\hat{Q} = Q - z(\kappa^r - \kappa^w)$. In other words, if we want to identify the implicit prices of individual amenities and calculate total expenditures, then we must rule out the possiblity of omitting any amenities. This is implausible, which brings us to our second key point. If most of the spatial variation in omitted amenities can be explained by variation in observed amenities, then we can obtain a reasonable approximation to expenditures even if $\hat{\beta}_2$ and $\hat{\gamma}_2$ are inconsistent estimators for β_2 and γ_2. Specifically, as the R^2 from regressing *z* on *A* approaches 1, $\eta \to 0$ and plim $\hat{Q} \to Q$. This illustrates why collecting data on a comprehensive set of amenities is essential to estimating national amenity expenditures.

IV. Results

A. United States Amenity Expenditures

Our estimates for U.S. amenity expenditures are based on the 950 locations in figure 1. Using all of the data from these locations, we estimate the model in (7)-(8) and calculate relative expenditures. To convert the relative expenditure measure into a measure of expenditure levels we must first address moving costs and define the subset of locations where each household would consider relocating.[30] Table 2

[30] A significant literature on migration highlights the role of amenities in the interregional re-distribution of population (Greenwood et al. 1991). See Molloy et al. (2011) for an overview of the literature and recent trends in the U.S. Baum-

reports the sensitivity of our estimates for expenditure levels to alternative normalizations for moving costs and choice sets, holding fixed the parameters estimated from (7)-(8).

Table 2: Implicit Expenditures on Amenities in the United States, 2000

Constraint for inclusion in the consideration set	Average number of locations considered	Share of Migrants 1995-2000	Expenditures / household: mean	Expenditures / household: st. dev.	Total Expenditures ($billion)
		A. Moving Costs Excluded			
(1) None	950	100%	6,032	3,081	632
(2) Emmigration Share > 0.1%	137	89%	5,855	3,156	614
(3) Immigration Share > 0.1%	135	89%	5,899	3,142	619
		B. Moving Costs Included			
(4) None	950	100%	5,550	3,010	582
(5) Emmigration Share > 0.1%	137	89%	5,341	3,102	560
(6) Immigration Share > 0.1%	135	89%	5,388	3,076	565

Notes: The first three columns describe the consideration set. For example, if the consideration set for a location is defined as all locations that accounted for at least 0.1% of emigration between 1995 and 2000, then the average consideration set consisted of 137 locations (out of 950). These consideration sets accounted for 89% of all emigration from 1995 to 2000. The last four columns report measures of real amenity expenditures based on each consideration set. See text for details.

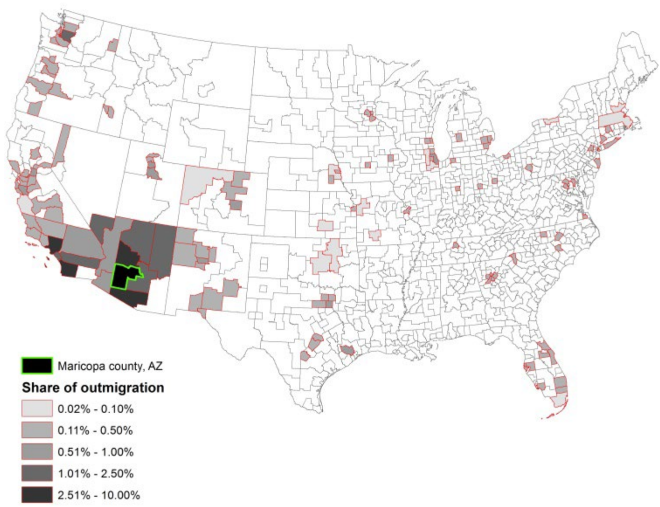
First, if we assume that people are freely mobile and fully informed about the spatial distribution of rents, wages, and amenities, then households face an unconstrained consideration set spanning all 950 locations.[31] In this case, real expenditures at a location are defined by the difference between relative expenditures at that location and relative expenditures at the least expensive location in the country; i.e. everyone shares the same minimum expenditure reference point. The results imply that the average U.S. household implicitly spent $6,032 on localized amenities in the year 2000 through some combination of higher housing prices, higher

Snow and Pavan (2012) also provides some interesting insights on migration patterns and wages between cities around the same time frame of our study using the National Longitudinal Survey of Youth.

[31] While households are assumed to be freely mobile within the contiguous United States, the cost of moving outside the U.S. is assumed to be prohibitively high. In principle, this constraint could be relaxed using data from Mexico and Canada. However, we doubt that this would lead to significant changes in our results once we control for moving costs.

property taxes, and lower wages (row 1). Aggregating over households implies a national measure of $632 billion.

Figure 2: Emigration Flows from Maricopa County, AZ



Notes: The figure provides an example of migration from Maricopa County, AZ to the rest of the United States between 1995 and 2000. Data are drawn from the Census Bureau's migration flow files. See text for details.

The $632 billion estimate will be too high if households do not consider all 950 locations in the United States due to the psychic cost of moving long distances or the perceived inability to find work in unfamiliar areas. With this in mind, we take a revealed preference approach to defining consideration sets. We approximate the subset of all locations that the average household in a particular location would consider moving to by analyzing the recent empirical emigration patterns for that location. Specifically, we restrict the consideration set for households in each location to include only those locations that accounted for greater than 0.1% of emigration between 1995 and 2000.[32] Figure 2 illustrates this approach using emigration from Maricopa County, AZ, which contains the Phoenix metropolitan area. The

[32] Migration flows were calculated for all pairwise combinations of locations using the Census Bureau's county-to-county migration flow files. Further robustness checks on the definition of a consideration set are discussed in section D.

consideration set is defined by the shaded locations, each of which accounts for at least 0.1% of emigration flows. Imposing this constraint limits the consideration set to include a mixture of nearby locations (both urban and rural) and other major metro areas that we would expect to be broadly salient to households, such as Chicago, Las Vegas, Los Angeles, New York, and Seattle. This pattern tends to be robust across origin counties is also consistent with evidence on migrant information networks (Pissarides and Wadsworth 1989).[33]

The 0.1% threshold reduces the number of locations the average U.S. household is assumed to consider from 950 to 137 and these locations account for 89% of all emigration flows. Interestingly, reducing the size of the consideration set by 85% only reduces our expenditure measure by 3% (comparing rows 1 and rows 2 in Table 2).[34] The reason for this can be seen from Figure 3. Expensive locations are predominantly located along the coasts and in resort areas in the Rocky Mountains. Inexpensive locations are predominantly located in the mid-west, south, and Appalachian regions. However, expensive and inexpensive locations are not completely stratified. There are inexpensive areas in California's central valley and expensive areas in the mid-west, for example. When expensive and inexpensive areas are close together, the migration between them tends to be significant. Thus, the consideration sets for most of the expensive locations contain some inexpensive locations, which define their reference points in our expenditure calculations. A second force behind the similarity in our expenditure measures in rows 1-2 is that some of the least expensive locations have significant migration flows. In particular, Wayne County, MI (i.e. Detroit) is one of the ten least expensive locations but accounts for significant migration flows to more than 400 other locations. The third row of Table

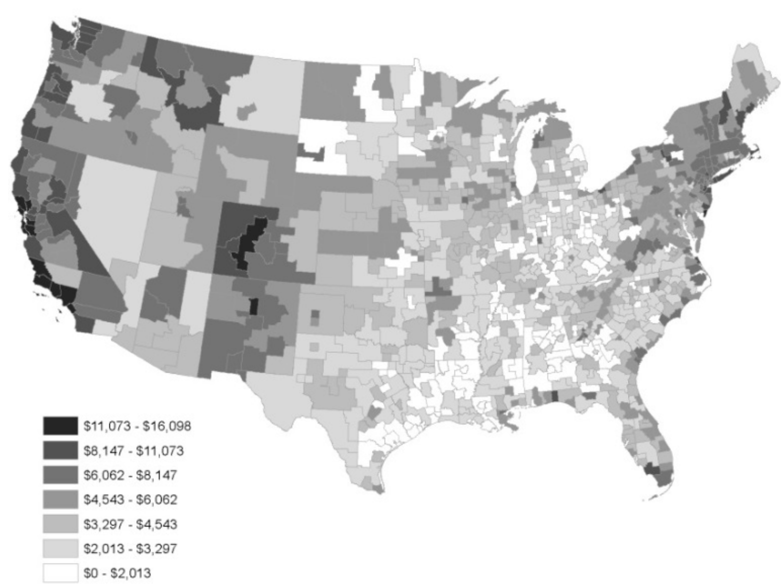
[33] An exception is that immigration-based consideration sets for rural locations are less likely to include distant metropolitan counties.

[34] Recall that real expenditures are defined by the difference between relative expenditures at a given location and relative expenditures at the least expensive alternative in the corresponding constrained consideration set.

2 shows that our calculations are virtually the same if we instead define consideration sets based on immigration flows. This is due to the similarity of immigration and emigration patterns.

The bottom half of Table 2 show how our results change when we account for the physical and financial cost of moving between each pair of locations. To calculate financial costs, we collected data on location-specific realtor fees, location-specific closing costs on housing sales, and search costs for home finding trips. To calculate the physical cost of a move, we used the calculator provided by movesource.com, along with information on the distance travelled, the weight of household goods transported based on the number of rooms in the origin location, and the cost of transporting cars (see full calculations in the appendix.)

Figure 3: Implicit Expenditures on Amenities by Location, 2000



Notes: Estimates for implicit amenity expenditures are based on 1995-2000 area-specific emigration shares of greater than 0.1% as a constraint for inclusion in the location specific consideration set (see text and table 3).

Our estimate for the physical cost of moving differs for every pair of locations.[35]

[35] The average cost of moving between a pair of counties is not symmetric. Direction matters because the physical cost of a

The average is \$12,123 and the standard deviation is \$2,729. We convert these one-time costs into annualized measures using a 37-year interval (reflecting the expected life years remaining for the average household head) and a real interest rate of 2.5%.[36] This implies the annual cost of a \$10,000 move is \$419.

When we account for the cost of moving, our estimates range from \$560 to \$582 billion (rows 4-6 of Table 2). If we assume that every household perceives Detroit to be its reference point, then \$582 billion is the more appropriate measure. While this assumption is not implausible given the media coverage of Detroit's decline, it will lead us to overstate expenditures for households who are unfamiliar with the area. With this in mind, our preferred estimates are the ones derived from the migration-based consideration sets with moving costs. They imply a range of \$560 to \$565 billion. Taking the midpoint, \$562, would suggest that implicit amenity expenditures were equivalent to 8.2% of personal consumption expenditures in 2000. The housing and labor markets each contribute substantially to this total. For instance, if we were to ignore housing price differentials when making the expenditure calculations our estimate would still be \$163 billion (29% of the total).

Finally, as a robustness check on the Dahl (2002) correction for Roy sorting, we repeat the estimation using an alternative procedure based on Bayer, Kahn, and Timmins (2011). Specifically, we multiply our raw wage data by the proportional correction factors they report by Census region and education level. This approach aims to remove the effect of latent human capital on wages prior to estimation. It increases our preferred expenditure measure from \$562 to \$591 billion. Thus, two different approaches to correcting for Roy sorting produce very similar results. This is not because the correction factors are small. If we do nothing to address the bias from Roy sorting, expenditures drop to \$422 billion. The large positive increase

move depends on the weight of goods transported which, in turn, depends on the number of rooms in the *origin* location.

[36] There are two reasons why actual moving costs may be lower for job-related moves. First, some employers pay for part or all of the cost. Second, some costs for job-related moves can be deducted from federal income taxes. By ignoring these forms of compensation, we will tend to overstate moving cost, and understate amenity expenditures slightly.

that occurs when we implement either correction is consistent with the intuition that higher-skilled workers are more likely to live in higher-amenity areas, biasing our expenditures measures toward zero.

B. Regional Amenity Expenditures

Table 3 summarizes regional variation in amenity expenditures, using the Census Bureau's nine divisions. Expenditures are based on the emigration consideration set summarized in row 5 of Table 2. Several interesting patterns emerge. First, the spatial concentration of expenditures supports the notion that the U.S. is a "coastal nation" in terms of nonmarket activity as well as market activity (Rappaport and Sachs, 2003). The coastal divisions account for nearly 70% of national amenity expenditures. Furthermore, expenditures per capita are generally higher in coastal areas, especially the Pacific division (CA, OR, and WA) which accounts for 14% of households but 28% of expenditures.

Table 3: Year 2000 Expenditures by Census Division

	New England	Middle Atlantic	East North Central	West North Central	South Atlantic	East South Central	West South Central	Mountain	Pacific
Mean income / household	$58,428	$56,229	$51,690	$47,532	$49,512	$41,677	$45,785	$48,527	$59,300
Amenity expenditures / household	$6,708	$6,733	$3,694	$3,789	$4,352	$2,775	$2,710	$5,751	$10,368
Amenity to income ratio	0.11	0.12	0.07	0.08	0.09	0.07	0.06	0.12	0.17
Number of households (million)	5.4	14.9	17.2	7.5	20.0	6.6	11.4	6.7	15.1
Amenity expenditures ($billion)	36	100	64	28	87	18	31	39	157
Share of U.S. expenditures	0.06	0.18	0.11	0.05	0.16	0.03	0.06	0.07	0.28

Notes: Estimates for amenity expenditures are based on the emigration consideration set summarized in row 5 of table 2 and described in the text. New England = {ME, NH, VT, MA, CT, RI}. Middle Atlantic = {NY, NJ, PA}. East North Central = {WI, IL, IN, OH, MI}. West North Central = {ND, SD, NE, KS, MO, IA, MN}. South Atlantic = {DE, MD, DC, VA, WV, NC, SC, GA, FL}. East South Central = {KY, TN, AL, MS}. West South Central = {TX, OK, AR, LA}. Mountain = {MT, ID, WY, CO, UT, NM, AZ, NV}. Pacific = {WA, OR, CA}.

Second, expenditures tend to be lower in regions that were in economic decline, such as the Rust Belt and southern Appalachia. For example, expenditures per household in the East North Central division, which roughly coincides with the Great Lakes region, are less than half the size of expenditures in the Pacific division.[37] Moreover, if we look within the Census divisions the ranking of locations by expenditures makes intuitive sense. The least expensive locations include Baltimore, Detroit, Houston, and county aggregates comprised of small cities and towns in the south and mid-west. The most expensive locations include San Francisco, New York, Los Angeles, and county aggregates containing small cities and towns that are known for their amenities, such as Aspen, Bozeman, Martha's Vineyard, and Santa Fe. More broadly, a weighted least squares regression of expenditures on income implies an elasticity of 0.95.[38]

C. Household Heterogeneity

To explore heterogeneity in amenity expenditures among households, we regress two measures of expenditures (full mobility, no moving cost [row 1, table 2]; and limited outmigration with moving cost [row 5, table 2]) on household demographics in the PUMS microdata.[39] For some specifications we also include industry and/or location fixed effects to determine how much of the demographic heterogeneity in expenditures can be explained by sorting based on industry locations and how much can be explained by local versus regional sorting. Table 3 reports the results from a set of location-specific population weighted regressions.

Columns (1) and (2) show results from regressing amenity expenditures on household demographics without including fixed effects. The results show that expenditures tend to be higher among Hispanic and Asian subpopulations as well as

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[37] Similarly, households in the Pacific, who also have the highest regional incomes, give up the largest fraction of their potential incomes to consume localized amenities (17%). Households in the West South Central region give up the smallest fraction (6%).

[38] The unit of observation is a location (N=950) and the weights are the number of households. The p-value on the coefficient for average household income is zero out to four decimal places and R^2=0.80. If we replace average household income in the regression with median household income or income per capita, the elasticities equal 0.95 and 0.94.

[39] The results using the immigration choice set (row 6 in table 2) instead of the emigration choice set are virtually identical which is why they are not reported here to conserve space in table 3.

among renters and people who are older, more educated, and wealthier in terms of non-wage income (which we assume is exogenous to location choice). Comparing the two columns reveals that accounting for moving costs tends to moderately increase the strength of these demographic associations. In contrast, we find that expenditures tend to be lower among black subpopulations, but this effect declines substantially in size and precision when we adjust for moving costs.

Columns (3) and (4) add industry fixed effects at the 2-digit NAICS level to absorb variation in expenditures that can be explained by workers sorting across locations based on proximity to certain types of employment. The coefficients on college degree decline by approximately one third, while the other coefficients are not substantively affected. Finding that relatively little heterogeneity in amenity expenditures can be explained by skill-based sorting on industries reinforces the importance of our strategy to account for the presence of Roy sorting in the amenity capitalization effect in wages.

The remaining columns add spatial fixed effects to account for sorting across Census divisions (columns (5) and (6)) and across MSAs (columns (7) and (8)). The results here reveal that almost all of the variation by race and ethnicity shown in columns (1) and (2) can be explained by population dispersion across broad geographic areas (e.g. higher population shares for Hispanic and Asian groups in coastal areas). Looking within metropolitan areas in columns (7) and (8) yields patterns that are consistent with the hypothesis that people who are older, wealthier, and better educated tend to choose to locate in areas that require them to spend more on amenities. This pattern is also consistent with localized sorting. For example, we find that college towns such as Blacksburg, VA ($7,112) and Boulder, CO ($6,993) tend to have above similarly elevated expenditures irrespective of the diverse regional surroundings.

Table 4: Amenity expenditures and household heterogeneity, 2000

Dep. variable:	Amenity expenditure by household							
	Baseline		Industry sorting		Industry, locational sorting			
					Census division		MSA	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Non-wage income	5.3***	5.9***	4.8***	5.3***	2.3***	2.7***	1.1***	1.1***
($1,000)	(0.9)	(1.0)	(0.8)	(0.9)	(0.5)	(0.5)	(0.4)	(0.4)
Black	513.6***	-208.0	-526.6***	-210.8	-77.1	147.2	-153.5**	-62.6
	(168.0.)	(174.7)	(171.4)	(177.0)	(128.2)	(131.8)	(68.1)	(70.7)
Hispanic	1435.2**	1712.5**	1475.6**	1770.2**	592.5**	896.6***	70.3	149.6**
	(658.1)	(700.6)	(670.6)	(713.6)	(236.4)	(259.6)	(65.2)	(68.6)
Asian	2322.9***	2705.9***	2338.1***	2711.8***	651.6***	1004.6***	7.2	109.3**
	(602.9)	(633.2)	(601.9)	(631.4)	(165.6)	(180.0)	(58.5)	(55.5)
Age	13.7***	16.01***	13.5***	16.2***	5.3***	7.1***	1.5***	2.0***
	(2.9)	(3.1)	(3.0)	(3.3)	(1.2)	(1.3)	(0.5)	(0.5)
College degree	488.0***	652.8***	325.8***	452.3***	207.2***	321.6***	127.7***	150.7***
	(88.8)	(92.2)	(67.7)	(69.7)	(44.8)	(46.8)	(26.7)	(28.6)
Renter	610.7***	687.1***	612.8***	687.8***	221.4***	282.2***	70.9	88.7
	(149.9)	(158.9)	(152.0)	(161.0)	(73.8)	(75.2)	(53.59)	(54.2)
Fixed effects	none	None	industry	industry	industry + division	industry + division	industry + MSA	industry + MSA
# of fixed effects			31	31	40	40	390	390
Moving cost	no	Yes	no	yes	no	yes	no	yes
Mean no. locations	950	137	950	137	950	137	950	137
Adj R^2	0.06	0.07	0.07	0.08	0.61	0.57	0.84	0.83
N. obs.	1,857,802	1,857,802	1,857,802	1,857,802	1,857,802	1,857,802	1,857,802	1,857,802

Notes: Estimates for amenity expenditures are based on the emigration consideration set summarized in row 5 of table 2 and described in the text. Data on household characteristics comes from the 5% PUMS data for households with at least one full-time worker above age 25. Regressions are weighted using household weights, and standard errors clustered by each of the locations in parentheses. * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

D. A Comparison to "Quality of Life" Rankings of Counties

To further examine the foundations for our national estimates in tables 2 and 3 and compare our findings to prior literature, we use our results to revisit Blomquist, Berger, and Hoehn's (1988) classic "quality of life" ranking of 253 urban counties by relative amenity expenditures.[40] Table 4 reports our top 20 and bottom 20 counties within this subset, along with the original BBH rankings.[41] This comparison provides an intuitive way to evaluate the impact of our data collection efforts and our refinements to the conventional approach to measuring compensating differentials. Alongside the rankings, we report the associated measures of relative expenditures; i.e. the metric that prior studies used to develop quality of life rankings. Since these measures are not normalized by moving costs or consideration set definitions, their levels are arbitrarily defined by the hedonic rent and wage specifications.

The relatively large negative numbers for low ranked counties illustrate how markets effectively compensate people for living in those areas. The top ranked county in our model is Marin County, CA and the bottom ranked county is Harris County, TX. A freely mobile household who chooses to live in Marin instead of Harris would pay an extra \$17,103 per year (11,966 + 5,137). To put this statistic in perspective, it is equivalent to 20% of the average household's income. The underlying thought experiment is the following: if the average Marin County household were to move to Harris, be paid according to its education and experience, and rent a house that is identical to the one it currently occupies, then the Marin County household would gain an extra \$17,103 of real income each year. What do Marinites "buy" when they sacrifice this income? Located directly north of San Francisco, Marin is a coastal county with a mild climate, clean air, some of the best public schools in California, a large share of land in parks, and the lowest rate of child mortality. Its residents also have easy access to the cultural and urban amenities of San Francisco.

[40] As explained earlier, our main objective is to measure amenity expenditures levels. We put "quality of life" in quotes to reiterate that additional assumptions are needed to interpret any ranking of counties by relative amenity expenditures as a universal ranking of the quality of life that all households would agree with.
[41] Complete econometric results and rankings for all counties can be produced from our data and code.

Table 5: Ranking 253 Urban Counties by Relative Expenditures

County, State	Core Business Statistical Area	Relative Expenditures (1)	Our rank (2)	BBH rank (3)
Marin, CA	San Francisco-Oakland-Fremont	11,966	1	142
San Francisco, CA	San Francisco-Oakland-Fremont	10,863	2	105
San Mateo, CA	San Francisco-Oakland-Fremont	9,726	3	112
Santa Clara, CA	San Jose-Sunnyvale-Santa Clara	9,197	4	88
Los Angeles, CA	Los Angeles-Long Beach-Santa Ana	8,883	5	58
Santa Barbara, CA	Santa Barbara-Santa Maria	8,805	6	22
Santa Cruz, CA	Santa Cruz-Watsonville	8,537	7	79
Alameda, CA	San Francisco-Oakland-Fremont	7,918	8	94
Orange, CA	Los Angeles-Long Beach-Santa Ana	7,580	9	41
Ventura, CA	Oxnard-Thousand Oaks-Ventura	7,224	10	23
New York, NY	New York-Northern New Jersey-Long Island	6,804	11	216
Contra Costa, CA	San Francisco-Oakland-Fremont	6,755	12	211
Monterey, CA	Salinas	6,306	13	16
San Diego, CA	San Diego-Carlsbad-San Marcos	6,216	14	27
Lane, OR	Eugene-Springfield	5,197	15	35
Nassau, NY	New York-Northern New Jersey-Long Island	5,136	16	60
Middlesex, NJ	New York-Northern New Jersey-Long Island	4,998	17	204
King. WA	Seattle-Tacoma-Bellevue	4,674	18	158
Clackamas, OR	Portland-Vancouver-Beaverton	4,629	19	138
Washington, OR	Portland-Vancouver-Beaverton	4,629	20	148
.	.	.	.	.
.	.	.	.	.
Porter, IN	Chicago-Naperville-Joliet	-2,266	234	205
Monroe, MI	Monroe	-2,305	235	208
Butler, OH	Cincinnati-Middletown	-2,455	236	121
Bibb, GA	Macon	-2,534	237	4
Lafayette, LA	Lafayette	-2,535	238	139
Shelby, TN	Memphis	-2,541	239	137
Wichita, TX	Wichita Falls	-2,584	240	210
Jefferson, MO	St. Louis	-2,592	241	242
Will, IL	Chicago-Naperville-Joliet	-2,700	242	230
Tarrant, TX	Dallas-Fort Worth-Arlington	-2,730	243	212
McLennan, TX	Waco	-3,079	244	189
Jefferson, AL	Birmingham-Hoover	-3,084	245	251
Galveston, TX	Houston-SugarLand-Baytown	-3,097	246	197
Etowah, AL	Gadsden	-3,159	247	157
Ouachita, LA	Monroe	-3,221	248	109
Brazoria, TX	Houston-SugarLand-Baytown	-3,395	249	250
East Baton Rouge Parish, LA	Baton Rouge	-3,860	250	168
Wayne, MI	Detroit-Warren-Livonia	-4,005	251	249
Jefferson, TX	Beaumont-Port Arthur	-4,861	252	196
Harris, TX	Houston-SugarLand-Baytown	-5,137	253	241

Notes: BBH rank denotes the corresponding county ranking from Blomquist, Berger, and Hoehn (1988).

More generally, the top counties tend to be located on the West Coast and/or in large metro areas, broadly consistent with the findings of Albouy (2016). Furthermore, 13 of the top 20 counties are in the San Francisco Bay area, the Los Angeles metro area, and the New York metro area. A quick comparison between columns (2) and (3) is sufficient to see that our measures of relative expenditures are positively correlated with those of BBH ($\rho = 0.29$). Therefore, the implied measures of real expenditures will also be similar. For example, if we treat the 253 counties studied by BBH as the consideration set and ignore moving costs, then our average measure of expenditures per household in the 253 urban counties is $6,670. If we use the CPI to convert BBH's 1980 results to year 2000 dollars, then their implied expenditure measure is $4,269.

However, there are three generic differences between our results and BBH. First, our rankings display higher spatial correlation, as can be seen from the clusters of adjacent San Francisco and New York counties in column (2). This is because our analysis quintuples the number of amenities and most amenities are spatially correlated. High spatial correlation is also consistent with the notion that spatial spillovers cause amenity levels to be similar in nearby locations. Second, most counties move dramatically in the rankings. Thirteen of our top 20 counties advance more than 50 places relative to BBH and nine advance more than 100 places. The largest increase is Rockland County, New York (#236 in BBH; #28 in our study). Rockland is approximately 10 miles north of Manhattan and is among the top 10 counties in the nation, ranked by median household income. Bibb County, Georgia has the largest decrease (#4 in BBH; #237 in our study). Its low ranking is not surprising. Bibb has the second highest rate of child mortality and 19% of its population falls below the poverty line. Finally, our measures for relative expenditures are also positively correlated with year 2000 income per capita ($\rho = 0.46$), consistent with empirical evidence on Tiebout sorting.[42] It should be noted that relative

[42] In comparison, the expenditure measures that BBH produced for 1980 are essentially uncorrelated with year 2000 income per capita ($\rho = -0.06$). We suspect this reflects the limited amenity data that were available at the time of the BBH study

amenities may have changed between the 1980 period of BBH and the 2000 period of our study. While Table 1 shows that most of the BBH amenities have similar means over this period, Diamond (2016) provides evidence that this similarity obscures important changes in the relative levels of several amenities across metro areas between 1980 and 2000. Furthermore she argues that areas that attracted higher skilled workers with higher wages over this time frame endogenously improved their amenities as well. Thus some of the differences between the BBH results and ours could reflect these changes.

E. Caveats

Our research design underscores the standard caveat that spatial equilibrium model results can be sensitive to choice set definitions. There are two dimensions to consider. First, the 0.1% migration thresholds that we used to define consideration sets could be too inclusive or too exclusive, and they may also mask heterogeneity in migration flows across different socioeconomic strata (e.g. systematic variation by income or skill).[43] A particular concern is that latent psychological costs of moving may prevent people from exploring job and house opportunities far from home. This concern is justified by national models of household sorting decisions that estimate a large disutility of moving long distances and interpret it as latent psychic costs of moving away from family, friends and familiar areas (e.g. Bayer, Keohane and Timmins 2009, Hamilton and Phaneuf 2015, Sinha, Caulkins and Cropper 2018). These psychic costs could cause our 0.1% migration thresholds to be too inclusive for the average household, which could then inflate our expenditure measures by erroneously including distant low-expenditure locations in the choice set.

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and changes in the spatial distribution of income and amenities between 1980 and 2000. See Kuminoff, Smith, and Timmins (2013) for a review of the evidence on income stratification from the literature on Tiebout sorting.

[43] The data and code in our supplemental appendix can be modified to consider any alternative consideration set.

To investigate the scope for psychic moving costs to inflate our results we repeat our expenditure calculations after further restricting the 0.1% migration share consideration sets to exclude any locations that fall outside a 250 mile radius drawn around the centroid of each household's current location. Physical proximity should mitigate the psychic cost of moving. The 250-mile radius is meant to approximate the sizes of geographic areas over which national sorting models typically assume there is no psychic cost of moving (e.g. states, major metropolitan regions). Using these localized consideration sets decreases our expenditure measure to $385 billion. We interpret this as a conservatively low estimate because the consideration sets only contain 67% of migration flows and an average of 82 locations. It is striking that reducing the number of locations in the average choice set by 91% only reduces estimated expenditures by 33%. The tightness of the bounds defined by our 250-mile radius and national consideration sets ($385 to $582 billion) underscores the importance of local spatial heterogeneity in amenity expenditure opportunities shown in Figure 3.

The second choice set dimension to consider is its granularity. Our estimates abstract from variation in amenity expenditures within each of the 950 locations that arises from more granular forms of spatial variation in amenities. Examples include discontinuities in public school quality across school attendance zones (Kuminoff and Pope 2014) and land use differences that arise from zoning discontinuities (Severen and Plantinga 2018). By smoothing over these differences, our location-specific estimates for average expenditures are likely to understate expenditures per household in relatively high expenditure neighborhoods and overstate expenditures per household in relatively low expenditure neighborhoods. This latent heterogeneity in expenditures seems most likely to result from localized variation in public goods (e.g. crime, schools), environmental externalities (e.g. salient point-sources of pollution) and urban amenities (e.g. whether a neighborhood is walking distance from dining and entertainment). In comparison, the amenities in Table 1 that we associate with climate, geography, and infrastructure tend to be relatively homogenous within the 950 locations we define. While we would expect the measurement errors in household-level expenditures to at least partially cancel out when we calculate location-specific averages, the direction and size of any lingering bias is ambiguous.

While both caveats apply broadly to the literature following Rosen (1979) and Roback (1982), our research design makes them more salient. It also suggests two possible directions for future research. First, our amenity database could be refined to add information on neighborhood level variation in some of the amenities (e.g. land use polygons, satellite measures of air pollution, school attendance zones). In principle, these data could be matched to more granular identifiers for households' residential locations in restricted access Census data to investigate how increasing spatial resolution affects the estimated distribution of expenditures. Second, the consideration set definitions could be refined by using administrative data to incorporate information on differences in migration flows across socioeconomic strata and/or surveying households to learn how they perceive their choice sets.

Another caveat is that our framework is not designed to decompose total amenity expenditures into vectors of implicit prices or expenditures for individual amenities. As shown in section III.B, a sufficient condition to identify expenditures on individual amenities is that no amenities are omitted. While this condition seems unrealistic, our framework could in principle be extended to recover expenditures on a subset of amenities by using instrumental variables to isolate exogenous variation in them.

F. Toward a Satellite Account for Nonmarket Amenities

Another potential direction for future research would be to extend our analysis to develop a formal satellite account for nonmarket amenities that would include a crosswalk to the National Income and Product Accounts (NIPA). Since NIPA's inception, economists have suggested expanding the accounts to provide a richer description of nonmarket goods and services that affect the quality of life (Kuznets 1934, Nordhaus and Tobin 1972, Eisner 1988, Jorgenson, Landefeld and Nordhaus 2006, Fleurbaey 2009, Stiglitz, Sen, and Fitoussi 2009). Growing support for this idea led the National Research Council (1999) to recommend that the United States construct satellite accounts for nonmarket goods and services, and the National Panel to Study the Design of Nonmarket Accounts (2005) set the top priorities to include environmental services, local public goods, and urban infrastructure. We have taken first steps toward developing a satellite account by building a national amenity database and measuring households' implicit expenditures on them.

Extending our work to design a formal satellite account with a NIPA crosswalk would require addressing two additional challenges. First, we would need to decompose our expenditure measure into housing, wage, and tax-related components that could be mapped into the corresponding NIPA categories. Second, we would need to repeat our data collection and estimation procedures at regular intervals to track how amenity quantities and expenditures change over time.

If these challenges could be addressed, the resulting satellite account could be used to track how households' consumption and expenditures on amenities evolves with income growth and macroeconomic shocks such as boom-bust cycles in the housing market.[44] This information could also help to calibrate macroeconomic models for evaluating national policies targeting features of environmental quality and other nonmarket amenities (Rogerson 2015, Shimer 2013, Smith 2012). A key challenge in developing such models is to incorporate opportunities for households to adjust their amenity bundles by moving. Our amenity database defines the opportunities for spatial adjustment at a scale that can be mapped into Census data.

[44] This satellite account would not be intended to capture the full impact of nonmarket amenities on the U.S. economy. For example, air pollution may reduce agricultural yields and recreation expenditures. Likewise, our measures would not capture expenditures on national public goods such as defense.

Likewise, the spatial distribution of our expenditure estimates can be used to define data moments that may help to calibrate parameters defining tradeoffs households are willing to make between consumption of private goods and local amenities.[45]

V. Conclusion

We set out to develop a methodology for estimating national amenity expenditures. Our estimate for the United States in the year 2000 ($562 billion) suggests that households reduced their potential expenditures on private goods by about 8% in order to consume nonmarket amenities at their home locations. This figure is several times larger than direct expenditures on local public goods via households' reported property tax payments ($137 billion). Thus, our results suggest that most spending on nonmarket amenities occurs indirectly through sales of complementary private goods, especially housing and labor. The labor market alone accounts for 29% of our total expenditure measure.

From a methodological perspective, our analysis has three broader implications. First, we find that spatial Roy sorting places a large downward bias on our expenditure measures. Higher skill workers are more likely to locate in higher amenity areas, causing the opposing effects of amenities and latent human capital to be conflated in the wage regression.[46] When we adapt the estimators from Dahl (2002) or Bayer, Kahn, and Timmins (2011) to mitigate the resulting bias, expenditures increase by more than $100 billion. This is striking because spatial Roy sorting has largely been ignored in prior research on pricing amenities and developing quality-of-life indices.[47] Second, researchers using data on housing prices from multiple

[45] To evaluate a prospective regulation targeting a particular amenity such as air quality, analysts may also need a direct estimate for expenditures on that amenity. Extracting such a measure from our model would require an instrument such as the ones developed by Chay and Greenstone (2005), Bayer, Keohane, and Timmins (2009), or Bento, Freedman, and Lang (2015).

[46] This mechanism provides a spatial analogue to Hwang, Reed, and Hubbard's (1992) model of occupational Roy sorting in which higher skill workers choose both pecuniary and non-pecuniary compensation.

[47] Bayer, Kahn, and Timmins (2011) make a similar observation, and Bayer, Keohane, and Timmins (2009) and Hamilton and Phaneuf (2012) provide notable counterexamples.

metropolitan areas should be aware of spatial variation in the real economic cost of homeownership. Our estimates for the annual user cost of housing vary across residential locations from as low as 4% to as high as 10%. Finally, we have developed a new way to use information on migration flows and the financial cost of moving to relax the assumption of free mobility that often underlies national models of spatial equilibrium in housing and labor markets.

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A1. Data

All of our data used in the hedonic wage and housing regressions is taken from the 5% sample of the public use microdata (PUMS) in the 2000 Census. We restrict our sample to non-farm households and person records above the age of 18 for which we construct a measure of hourly wages and monthly housing expenditure.

i. *Hourly wages*

We compute implied hourly wages for full-time workers from self-reported annual income, weeks worked and hours worked per week. Full-time workers are defined using the standard BLS definition as persons who work at least 35 hours or more per week.

In order to assess the impact of regional variations in the burden of federal and state income taxes on quality of life estimates, we derive a measure of hourly after-tax wages. For this purpose, we use estimates of average marginal tax rates for federal and state income taxes for 1999 from the NBER's TAXSIM database. We also account for differences in the level of state excise tax rates which are obtained from from the Book of States (Council of State Governments, 2000) minus food tax exemptions (share weighted).[48] The summary statistics of hourly after-tax wages across our three samples are also shown in table A1.

Table A1: Person record summary statistics

	Mean	*Std. Dev.*	*Min.*	*Max.*
BBH counties				
Age	39.48	13.2	18	93
Weeks worked in 1999	45.11	12.7	1	52

[48] See: Council of State Governments. 2000. *The Book of the States, Vol 33.* The Council of State Governments, Lexington, KY.

Hours per week in 1999	39.93	11.97	5	99
Wage/salary income in 1999	34,592	40,794	10	347,000
Gross hourly wage	19.02	24.19	1.50	500
Hourly wage (after federal taxes)	14.15	17.98	1.09	385.70
Average marginal federal tax rate (%)	25.59	1.61	20.29	27.51
N. Obs	3,223,602			
MSAs				
Age	39.74	13.35	18	93
Weeks worked in 1999	45.00	12.81	1	52
Hours per week in 1999	39.82	11.95	5	99
Wage/salary income in 1999	32,775	38,538	10	385,000
Gross hourly wage	18.10	23.05	1.50	500
Hourly wage (after federal taxes)	13.49	17.15	1.09	390.70
Average marginal federal tax rate (%)	25.46	1.63	20.29	27.51
N. Obs	5,827,743			
Conterminous US				
Age	39.80	13.37	18	93
Weeks worked in 1999	44.89	12.89	1	52
Hours per week in 1999	39.83	12.02	5	99
Wage/salary income in 1999	32,047	38,250	20	385,000
Gross hourly wage	17.62	22.51	1.50	500
Hourly wage (after federal taxes)	13.17	16.84	1.09	395.95
Average marginal federal tax rate (%)	25.39	1.59	20.29	27.51
N. Obs	6,630,030			

ii. *Local cost-of-living and non-housing goods*

Although the cost of living varies substantially across regions, wages are usually deflated using a single, nation-wide deflator, such as the CPI-U calculated by the BLS. The use of a nation-wide deflator is potentially problematic given that more than 40% of the CPI-U is determined by housing costs. The local CPI-U released by the BLS and the ACCRA Cost-of-Living Indices are the two local price indices that are most widely used in empirical work. However, both measures have shortcomings: the local CPI-U is only produced for 23 of the largest metropolitan areas. Furthermore, there are slight differences in the composition of the underlying consumption baskets across cities and the index is normalized to 1 in a given year, thus precluding cross-sectional comparisons. The use of the ACCRA CoLI, on the other hand, might prove problematic due to features of its theoretical design, data collection, and sampling design, as discussed by Koo, Phillips, and Sigalla (2000).[49]

The lack of reliable regional cost-of-living indices thus means that most empirical studies do not deflate nominal wages beyond the adjustment in the cost of housing services, as measured by local rents. However, recent work on urban compensating differentials suggests that non-housing goods might also play an important role in determining the local cost-of-living. In order to account for the local variation in the price of non-housing goods, we follow Moretti (2013) who proposes an index that allows the cost of housing and non-housing consumption to each vary across metropolitan areas. While the city-level CPI-U published by the BLS is limited in its geographical coverage, it can still be used to estimate what share of non-housing costs varies with the local cost of housing. The local CPI-U for city j in year t is a weighted average of housing costs, HC_j^t, and non-housing costs (NHC_j^t) such that

$$\text{(A1)} \qquad \mathrm{BLS}_j^t = \alpha \mathrm{HC}_j^t + (1-\alpha)\mathrm{NHC}_j^t,$$

where α is the CPI weight used by the BLS for housing expenditure. Non-housing costs can now be expressed as consisting of an element that varies systematically with housing costs and an element that evolves independently form housing cost, i.e. $\mathrm{NHC}_j^t = \pi \mathrm{HC}_j^t + \upsilon_j^t$. Using first-differenced prices to avoid non-stationarity then gives the regression $\Delta \mathrm{BLS}_j^t = \beta \Delta \mathrm{HC}_j^t + \varepsilon_j^t$, which in turn can be used to back-

[49] Koo, J., K.R. Phillips, and F.D. Sigalla. 2000. "Measuring Regional Cost of Living." *Journal of Business and Economic Statistics*. 18(1): 127-136.

out an estimate of π by estimating $\hat{\beta}$, since $\hat{\pi} = \frac{\hat{\beta} - \alpha}{1 - \alpha}$. We use panel data on the small sample of 23 MSAs for which a local BLS CPI is available from 1976-2000 to obtain the fixed-effects estimate for β which yields:

$$\text{(A2)} \qquad \Delta \text{BLS}_j = \underset{(0.07)}{1.792} + \underset{(0.01)}{0.619} \quad \Delta \text{HC}_j + \varepsilon_j \quad R^2 = 0.74.$$

With $\alpha =$ 0.427 according to the BLS CPI-U weights in 2000, we can then impute the systematic component of non-housing costs for all MSAs based on their housing cost, i.e. $\hat{\pi}\text{HC}_j^{2000}$ with $\hat{\pi} = 0.332$. Lastly, we compute a local price index as the weighted sum of the cost of housing, the component of non-housing costs that varies with housing, and the component of non-housing costs that does not vary with housing. Our parameter estimates are close to Moretti's estimates of $\hat{\pi} =$ 0.35 which corresponds to $\hat{\beta} =$ 0.63 in 2000.[50]

iii. *Self-reported housing values*

In the long form of the 2000 Census (question 51), housing values are self-reported in 24 intervals from ``less than $10,000" to a top-coded category of ``$1,000,000 or more". This implies that the data on housing values, our dependent variable for the housing hedonic regressions, is both interval censored and left- and right-censored. Using an ad-hoc OLS regression on the midpoints of the intervals of such grouped data could lead to inconsistent estimates, because it might not adequately reflect the true uncertainty concerning the nature of the exact values within each interval and because it might also inadequately deal with the left- and right-censoring issues in the tails. We address this issue by comparing the

[50] Albouy (2009) uses ACCRA data to run a regression similar to equation (2) and obtains a slightly smaller value of $\hat{\pi} =$ 0.26.

parameters from estimating the housing regression via OLS using the interval mid-points to those from using the more appropriate maximum-likelihood interval estimator.

Table A2: Housing summary statistics

	Mean	*Std. Dev.*	*Min.*	*Max.*
BBH counties				
Number of rooms	5.41	2.03	1	9
Number of bedrooms	2.57	1.12	0	5
Acreage	0.86	2.02	0.1	15
Property value	106,632	153,198.1	5,000	1,000,000+
Gross rent	222.59	393.54	4	2,833
Effective property tax rate (%)	1.37	0.94	0	11.49
User cost of housing (%)	4.53	0.65	3.22	13.20
Price-rent ratio	22.08	3.17	31.06	7.58
Monthly housing expenditures ($)	665.47	479.67	50	4,290.42
Workers per household	1.75	1.39	0	4
N. Obs	2,395,116			
MSAs				
Number of rooms	6.18	1.69	1	9
Number of bedrooms	2.98	0.9	0	5
Acreage	1.31	2.80	0.1	15
Property Value	96,201	136,991	5,000	1,000,000+
Gross rent	190.69	358.33	0	2,833
Effective property tax rate (%)	1.28	0.93	0	11.49
User cost of housing (%)	4.47	0.62	3.22	13.20
Price-rent ratio	22.37	3.25	31.06	7.58
Monthly housing expenditures ($)	600.15	463.32	50	3,926.11
Workers per household	1.77	1.38	0	4
N. Obs	4,392,406			
Conterminous US				
Number of rooms	6.15	1.68	1	9
Number of bedrooms	2.97	0.89	0	5
Acreage	1.52	3.08	0.1	15
Property value	92,535.94	132,544	5,000	1,000,000+
Gross Rent	175.19	340.25	0	2,917
Effective property tax rate (%)	1.28	0.95	0	12.49
User cost of housing (%)	4.48	0.68	3.22	13.20
Price-rent ratio	22.32	3.24	31.06	7.58
Monthly housing expenditures ($)	571.19	450.82	50	3,926.11
Workers per household	1.76	1.38	0	4
N. Obs	5,163,123			

As a result of our large sample sizes combined with a large number of intervals, we do not find a significant differences between the two sets of estimates. This suggests that the consequences of grouping are unlikely to be important for our application. Furthermore, the root mean-square errors for the two estimators are very similar which suggests that the loss of precision due to using interval midpoints is relatively small and confirms the large-sample findings of Stewart (1983).[51]

Finally, although owners tend to overstate the value of their homes compared to actual sales values, Kiel and Zabel (1999) provide evidence that the magnitude of the overvaluation is relatively small (5%), and—more importantly—that the valuation errors are not systematically related to characteristics of the homeowners, structural characteristics of the house, or the neighbourhood.[52] This implies that empirical estimates based on self-reported house values will provide unbiased estimates of the hedonic prices of both house and amenity characteristics. The summary statistics for the housing sample are reported in table A2.

iv. Geography

Table A3 reports summary statistics for three groups of counties. The first group consists of the same 253 urban counties studies by BBH. These counties cover less than 10% of land area in the lower 48 states, but account for almost half of its population. They are a subset of the second group comprising all metropolitan statistical areas (MSA). Using the MSA definitions from the 2000 Census, metropolitan counties contain 80.3% of the U.S. population and 29.7% of its land area. The final group of counties covers the contiguous U.S. This is our study area.

[51] We adjust the top-coded housing values by multiplying them by 1.5. See Stewart, M.B. 1983. "On Least Squares Estimation when the Dependent Variable is Grouped." *Review of Economic Studies*. 50(4): 737-753.

[52] See Kiel, K.A. and J.E. Zabel. 1999. "The Accuracy of Owner-Provided House Values: The 1978-1999 American Housing Survey." *Real Estate Economics*. 27(2): 263-298.

Table A3: Geographic Coverage and Population Coverage

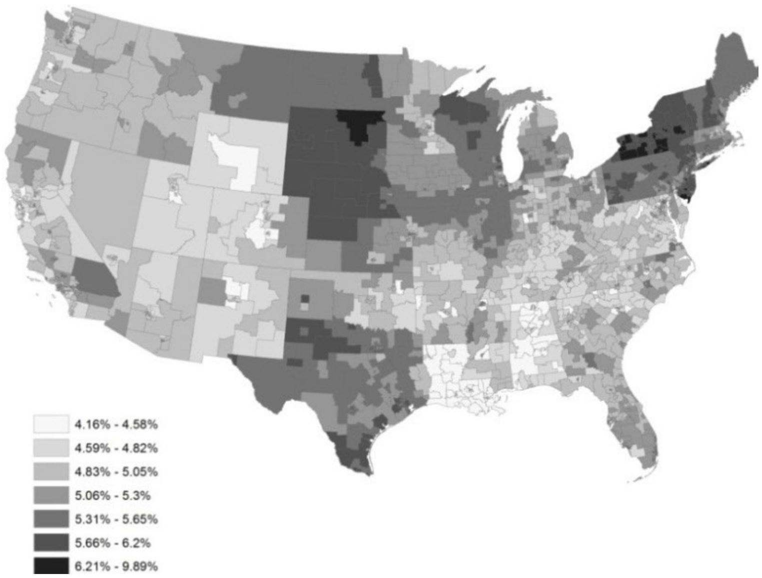
		Geography		
		BBH counties	*Metropolitan counties* *	*All counties* †
No. of counties		253	1,085	3,108
No. of PUMAs		1,061	1,835	2,057
PUMAs per county		4.19	1.69	0.67
Population	1980	110,617,710	170,867,817	226,545,805
	2000	138,618,694	224,482,276	279,583,437
Pop. Coverage ‡	1980	48.8%	75.4%	100.0%
	2000	49.6%	80.3%	100.0%
Pop. Density (per mi^2)	1980	419	197	77
	2000	525	259	94
Land area (mi^2)		263,840	865,437	2,959,064
Water area (mi^2)		25,273	61,081	160,820
Total area (mi^2)		289,113	926,518	3,119,885
Areal coverage‡		9.3%	29.7%	100.0%
No. obs from PUMS	workers	4,833,916	8,875,172	10,198,936
	households	2,587,457	4,795,515	5,484,870

Notes: PUMAs must have a minimum census population of 100,000. * Using 1980 or 2000 OMB definitions of metropolitan statistical areas. † Contiguous United States only. ‡ Alaska and Hawaii are excluded.

v. Spatial Variation in the User Cost of Housing

Figure A1 shows how our estimate for the user cost of housing varies across the contiguous United States, by PUMA.

Figure A1: Spatial Variation in the User Cost of Housing, by PUMA



Note: The user cost of housing is the discount factor by which imputed rents are calculated from self-reported house values. Each shade on the map represents a range of values. See the main text for additional details.

A2. Moving Costs

We calculated average moving costs between counties by combining information on both the average physical and financial costs of moving. The physical cost of the move includes cost of transporting household goods, vehicles and the people in the household. The financial costs included information on realtor fees, location-specific closing costs and search costs from trips to search for a new residence.

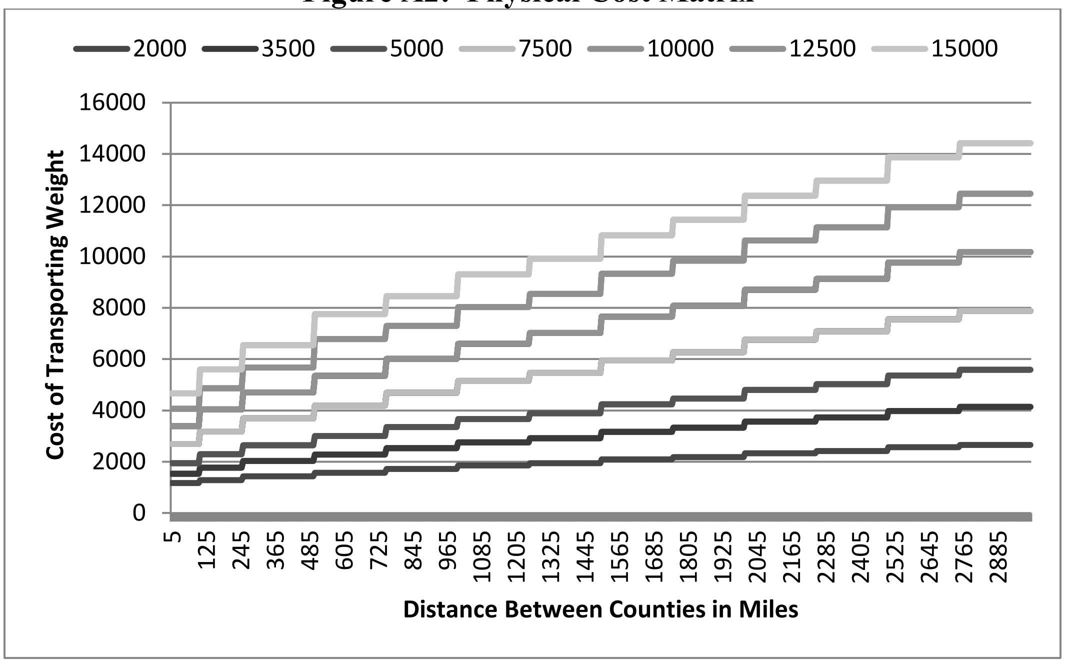
ii. *Physical Costs*

The first step in calculating physical costs was to calculate the linear distance in miles between the population weighted centroids from each county in the United States to every other county. The next step was to use the PUMS data to calculate the average number of bedrooms and the fraction of renters in each of the counties.

Based on the average number of bedrooms in a county, we used the "weight estimator guide" at www.movesource.com to calculate the weight (in pounds) that the average sized household would be transporting from their "origin" county to their "destination" county. The average number of bedrooms in the counties ranged from a minimum of 1.36 to a maximum of 3.46. Based on the weight estimator guide, counties with an average number of bedrooms between 1 and 2 were assigned a transportation weight that varied linearly between 3,500 (for a 1 bedroom) and 5,000 (for a 2 bedroom) pounds. For counties with an average number of bedrooms between 2 and 3, transportation weight ranged between 5,000 and 7,500 pounds and for counties with an average number of bedrooms between 3 and 4 the transportation weight ranged between 7,500 and 10,000 pounds. We assumed that renters in a county shipped on average 1500 pounds less than homeowner households such that our calculated cost to move between counties also depends on the fraction of renters in the origin county. The underlying parameters from the movesource.com moving calculator were used to calculate the cost of shipping based on the weight of the move and the distance between counties for each origin/destination county combination. Figure A2 shows the cost of transporting various weights (between 2000 pounds and 15000 pounds) for distances between 5 miles and 3000 miles using the movesource.com calculator.

We also assumed that all households transport two vehicles to their new location. The cost of this transportation was based on the IRS's mileage rate for the year 2000 which was 32.5 cents a mile. Thus the vehicle transportation cost was calculated by multiplying 65 cents by the number of miles between the origin and destination counties. Finally, we assume that a household stays in a hotel every 500 miles along their move and incurs some additional daily expenses for food, etc. We apply the average room rate in 2000 (according to the American Hotel and Lodging Association) of $86 to each of these hotel stays and assume that a household's per diem is $100 per 500 miles. Thus, total physical costs of moving are the summation of the cost of transporting household goods, transporting vehicles, hotel stays and per diem costs as a household moves from an origin county to a destination county.

Figure A2: Physical Cost Matrix



ii. *Financial Costs*

Financial costs also vary by renter and homeowner. We assume that homeowners (not renters) must pay closing costs to sell their house in their origin county. Our calculations are based on Bankrate.com's 2005 survey which provides average closing costs by state. We also assume that homeowners (not renters) pay a real estate agent 3% to facilitate selling their house and a real estate agent 3% to buy a house. Thus, we calculate these costs as 3% of the average housing value in the origin county and 3% of the average housing value in the destination county. We assume that both homeowners and renters pay to search for a new residence. These "finding costs" for moves within 60 miles, between 60 and 180, between 180 and 500, between 500 and 1000, and greater than 1,000 miles are assumed to be 0, 250, 500, 1,000 and 2,000 dollars. These finding costs reflect our best guess for the search costs when travel is local, requires at least a day, requires an overnight stay, or likely requires plane tickets in order to look for a new residence in the destination county.

Total financial costs are calculated by summing up the financial costs of searching for a new residence (for renters and homeowners) and the costs of buying and selling a home (for homeowners only). The weight assigned to the homeowner and the renter calculations is again based on the fraction of renters in a county. The total moving cost used in the final robustness check of the paper is calculated by summing the physical and financial costs we have described above.

A3. Amenity Database and Stata Code

The Stata file *amenity.dta* contains our county level database on amenities. The zip file *results.zip* contains data and code to replicate all of the tables in the paper. It also includes instructions to produce expenditure measures for specific counties, PUMAs, or puma-county unions. See the *readme.pdf* file for details.

A4. Additional Results

Table A4 reports coefficients and standard errors on amenities from equation (8). Since the dependent variables in the first stage of our model are measured in natural logs we apply the Halvorsen-Palmquist adjustment to the dependent variables prior to second stage estimation to convert the "percentage" coefficients into dollar values. Thus, the coefficients in Table A4 define the dollar value differentials in monthly rents and hourly wages associated with one-unit changes in each amenity. The sample size is 950 and the R-squared is 0.59 for the wage regression and

0.83 for the housing regression. We caution against direct economic interpretations of the coefficients as the amenities are correlated with each other and probably with unobserved amenities. Further, the standard errors do not have the usual statistical interpretation as sampling error because these regressions are based on the entire population of locations in the contiguous United States. See Table 1 and the main text for variable definitions and sources.

Table A4: Results from the Amenity Regressions

	Wage Regression		Housing Regression	
	Coefficient	*Std. Error*	*Coefficient*	*Std. Error*
	(1)	(2)	(3)	(4)
GEOGRAPHY AND CLIMATE				
Mean precipitation (inches p.a., 1971-2000)	-0.00481	(0.0024)	-0.04027	(0.3930)
Mean relative annual humidity (%, 1961-1990)	-0.00068	(0.0053)	2.623758	(0.8882)
Mean annual heating degree days	-3.91E-06	(0.0000)	-0.05182	(0.0063)
Mean annual cooling degree days	0.000168	(0.0001)	-0.15483	(0.0129)
Mean wind speed (m.p.h., 1961--1990)	0.07194	(0.0222)	17.7336	(3.6985)
Sunshine (% of possible)	-0.00839	(0.0058)	2.980531	(0.9758)
Heavy fog (no. of days with visibility ≤ 0.25 mi.)	-0.007	(0.0031)	-3.05563	(0.5126)
Percent water area	-0.00734	(0.0023)	0.150983	(0.3872)
Coast (=1 if on coast)	0.22782	(0.0824)	65.38208	(13.7446)
Non-adjacent coastal watershed (=1 if in watershed)	0.191503	(0.0540)	28.32203	(9.0130)
Mountain peaks above 1,500 meters	6.94E-05	(0.0008)	-0.12432	(0.1320)
Rivers (miles per sq. mile)	0.33689	(0.2266)	-60.0454	(37.8055)
Federal land (percentage of total land area)	0.002121	(0.0015)	0.367521	(0.2535)
Wilderness areas (percentage of total land area)	-0.00642	(0.0070)	0.695603	(1.1701)
National Parks (percentage of total land area)	-0.0044	(0.0070)	2.636924	(1.1703)
Distance (km) to nearest National Park	0.001226	(0.0004)	0.007341	(0.0696)
Distance (km) to nearest State Park	0.004899	(0.0013)	-0.25622	(0.2171)
Scenic drives (total mileage)	-0.00685	(0.0265)	-0.9234	(4.4174)
Average number of tornados per annum (1950-2004)	-0.02984	(0.0675)	-13.5571	(11.2667)
Property damage from hazard events ($000s, per sq. mile)	-1.90E-07	(0.0000)	3.08E-05	(0.0000)
Seismic hazard (index)	-0.00019	(0.0001)	0.021329	(0.0184)
Number of earthquakes (1950-2000)	0.00235	(0.0023)	-0.21725	(0.3800)
Land cover diversity (index, range 0-255)	-0.00054	(0.0005)	-0.07774	(0.0853)
ENVIRONMENTAL EXTERNALITIES				
NPDES effluent dischargers (PCS permits, 1989-1999)	0.001081	(0.0010)	-0.37608	(0.1616)
Landfill waste (metric tons, 2000)	1.04E-06	(0.0000)	0.000209	(0.0002)
Superfund sites	0.021377	(0.0096)	5.477996	(1.5947)
Treatment, storage and disposal facilities	0.00189	(0.0008)	-0.08241	(0.1399)
Large quantity generators of hazardous waste	-0.00059	(0.0002)	0.051985	(0.0302)
Nuclear power plants	0.054971	(0.0908)	-6.6399	(15.1425)
PM2.5 (µg per m^3)	0.021281	(0.0076)	-4.97903	(1.2635)
PM10 (µg per m^3)	0.01028	(0.0050)	0.086907	(0.8305)
Ozone (µg per m^3)	0.003089	(0.0021)	0.266856	(0.3480)
Sulfur dioxide (µg per m^3)	0.017324	(0.0197)	-6.97857	(3.2914)
Carbon monoxide (µg per m^3)	0.000992	(0.0007)	0.232968	(0.1216)
Nitrogen dioxide (µg per m^3)	-0.02277	(0.0064)	2.007788	(1.0677)
National Fire Plan treatment (percentage of total area)	-0.07021	(0.0422)	0.336637	(7.0321)
Cancer risk (out of 1 million equally exposed people)	0.005898	(0.0218)	0.123181	(3.6292)
Neurological risk	-0.07458	(0.1947)	-38.085	(32.4728)
Respiratory risk	0.026031	(0.0120)	8.529988	(1.9965)

LOCAL PUBLIC GOODS				
Local direct general expenditures ($ per capita)	0.12074	(0.0252)	16.69893	(4.2092)
Local exp. for hospitals and health ($ per capita)	1.15E-06	(0.0001)	-0.00309	(0.0130)
Local exp. on parks, rec. and nat. resources ($ pc)	-3.5E-05	(0.0001)	-0.00425	(0.0240)
Museums and historical sites (per 1,000 people)	0.015623	(0.0060)	-0.74254	(1.0021)
Municipal parks (percentage of total land area)	0.034804	(0.0190)	22.00409	(3.1715)
Campgrounds and camps	-0.01629	(0.0049)	0.671194	(0.8219)
Zoos, botanical gardens and nature parks	-0.01608	(0.0187)	3.11851	(3.1180)
Crime rate (per 100,000 persons)	1.94E-05	(0.0000)	-0.001	(0.0013)
Teacher-pupil ratio	-4.21125	(1.0199)	-369.679	(170.1414)
Local expenditure per student ($, 1996-97 fiscal year)	-0.00023	(0.0002)	0.027945	(0.0402)
Private school to public school enrollment (%)	1.303005	(0.2828)	475.888	(47.1810)
Child mortality (per 1000 births, 1990--2000)	0.029934	(0.0142)	-13.9888	(2.3618)
INFRASTRUCTURE				
Federal expenditure ($ pc, non-wage, non-defence)	-2.89E-06	(0.0000)	-0.00022	(0.0006)
Number of airports	-0.02458	(0.0190)	-8.98683	(3.1654)
Number of ports	0.076638	(0.0439)	-32.9929	(7.3223)
Interstate highways (total mileage per sq. mile)	-0.5889	(0.4133)	-59.0551	(68.9466)
Urban arterial (total mileage per sq. mile)	0.302337	(0.1283)	-49.1626	(21.4098)
Number of Amtrak stations	-0.04051	(0.0234)	-7.89242	(3.8956)
Number of urban rail stops	-0.0047	(0.0020)	0.093274	(0.3336)
Railways (total mileage per sq. mile)	-0.23618	(0.0573)	-37.1567	(9.5507)
CULTURAL AND URBAN AMENITIES				
Number of restaurants and bars (per 1,000 people)	-0.45898	(0.0837)	23.73215	(13.9607)
Theatres and musicals (per 1,000 people)	-0.88378	(1.4072)	764.2094	(234.7595)
Artists (per 1,000 people)	0.149605	(0.1131)	51.07887	(18.8708)
Movie theatres (per 1,000 people)	-4.73235	(1.6602)	461.7623	(276.9558)
Bowling alleys (per 1,000 people)	-1.58687	(1.3756)	-789.71	(229.4820)
Amusement, recreation establishments (per 1,000 people)	-0.091	(0.0665)	-19.5634	(11.0915)
Research I universities (Carnegie classification)	0.007666	(0.0031)	1.930234	(0.5184)
Golf courses and country clubs	-0.03382	(0.0059)	-0.16907	(0.9851)
Military areas (percentage of total land area)	-0.29959	(0.0573)	52.87875	(9.5544)
Housing stress (=1 if > 30% of households distressed)	-0.02292	(0.0803)	-18.7777	(13.4008)
Persistent poverty (=1 if > 20% of pop. in poverty)	0.035727	(0.0607)	9.500817	(10.1252)
Retirement destination (=1 if growth retirees > 15%)	0.004937	(0.0013)	0.575421	(0.2135)
Distance (km) to the nearest urban center	-0.00246	(0.0006)	-0.5988	(0.1050)
Incr. distance to a metropolitan area of any size	-0.00106	(0.0003)	-0.16107	(0.0500)
Incr. distance to a metro area > 250,000	-0.00129	(0.0003)	-0.06242	(0.0529)
Incr. distance to a metro area > 500,000	-0.00061	(0.0002)	-0.15754	(0.0291)
Incr. distance to a metro area > 1.5 million	-0.00481	(0.0024)	-0.04027	(0.3930)