Valuing the Consumption Benefits of Urban Density

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ABSTRACT: This paper estimates the consumption value of urban density by combining travel microdata with Google's local business data. This dataset allows the integration of travel costs into a discrete choice model for restaurants. In high density areas, consumers enjoy large benefits from visiting places that they prefer, and relatively smaller gains from shorter trip times. This implies that urban policies encouraging higher density living mostly result in higher gains from variety, instead of lower travel times. These results demonstrate the importance of non-tradable consumption in explaining the value of cities, and represent the first estimates of the gains from variety in the service sector.

Key words: consumer cities, gains from variety, urban density, accessibility, travel demand.

JEL classification: D12, R41

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1. Introduction

In 2010, 80.7% of Americans lived in urban areas, covering only 3.0% of the US land mass. To explain this sharp agglomeration pattern, empirical research has focused on measuring how larger, denser cities make workers more productive.[1] The benefits from density, however, are not limited to workers. Consumers may also gain from density, through better access to a variety of goods and services (Glaeser, Kolko, and Saiz, 2001). Such consumer-based agglomeration forces are now part of the mainstream discussion among urban analysts and policy-makers, but being inherently hard to measure, they receive less academic attention than agglomeration forces increasing workers' productivity. So while the potential for consumption amenities to drive urban success is an area of vigorous policy debate,[2] empirical evidence remains scarce as to the origin and importance of the consumption advantage of cities.

This paper sets out an approach to estimating the consumption value of urban density. The estimation uses travel data and exploits the recent availability of detailed online microgeographic data on local businesses. The methodology captures both the gains from shorter trip times and the gains from increased choice in denser areas (so-called 'gains from variety'), and identifies an individual's willingness to pay for access to a preferred location from the extra travel costs that she incurred to reach it.

The paper provides estimates of the gains from density in the US restaurant industry, a prominent part of the urban service sector. This exercise is of interest for three reasons. First, American households spend almost a quarter[3] of their income on non-tradable services such as restaurants, live entertainment, and professional services (e.g. medical care) requiring face-to-face interactions. The paper is the first to measure the importance of variety in non-

[1]See for instance Melo, Graham, and Noland (2009) for a meta-analysis of estimates of agglomeration economies, and Combes, Duranton, and Gobillon (2011) for a survey of key empirical issues.

[2]For instance, Clark (2003) shows that cities providing more natural and constructed amenities experience faster population growth. Carlino and Saiz (2008) find that metropolitan areas that are attractive to tourists (likely because of consumer amenities) are also growing faster. Moretti (2012) and Diamond (2016), however, argue that local production shocks drive urban success, with higher consumption amenities being a largely endogenous outcome.

[3]I exclude legal services and some other professional services from this computation. I include health care services, which account for 16.7% of total personal consumption expenditures, meals plus drinks with purchased meals, which account for 5.2%, and personal care services, which account for 0.9%. Sports, museums, live entertainment and laundry account together for another 1.4%. These numbers are from the Personal Consumption Expenditure (PCE) 2013 Tables of the Bureau of Economic Analysis.

tradables, and the results suggest that it represents most of the consumption value of modern cities. This finding stands in contrast to existing urban theories, which only model variety in the tradable sector.[4]

Second, the particular channels through which consumers benefit from density have important implications for urban policy and for our understanding of how individuals use their spatial environment. Intuitively, spatial proximity to restaurants in dense urban areas should allow individuals to take very short trips to eat out. However, a vast literature reviewed in Ewing and Cervero (2010) documents the strikingly small ability of higher density to reduce trip length in practice. The paper explains this finding by showing that urban density reduces the travel costs of substituting among destinations that one prefers, and that such gains from variety are larger than gains from shorter trips. This trade-off between gains from variety and gains from shorter trips implies that increasingly popular policy attempts at reducing vehicle travel by encouraging higher density living should have relatively small impacts.

Third, estimates of the gains from variety in the service sector contribute to an emerging literature estimating the gains from variety in consumer goods (Broda and Weinstein, 2006, 2010).

To estimate the welfare gains from urban density, I specify a discrete choice model of demand for travel destinations. The analysis focuses on restaurants because of data availability, but they account for more than 5% of household expenditures. In the model, each restaurant receives a logit utility shock, and locations farther away from an individual are more expensive because of travel costs. Individuals face a trade-off between the gains from visiting a preferred restaurant and the costs of a longer trip. The key parameter of the model is an elasticity of substitution between restaurants, estimated by maximum likelihood. This estimation exercise does not require data on restaurant choice, only on trip length. Using transport costs to provide variation in restaurant prices solves an endogeneity problem that typically arises when estimating an elasticity of substitution, due to the unobserved relationship between higher prices and better quality. If individuals always travel to the closest restaurant, then

[4]Prominent examples of such models are in the "New Economic Geography" literature (e.g. Helpman, 1998), that builds on Krugman's (1991) seminal contribution.

restaurants must be perfect substitutes and there are no gains from restaurant variety in dense areas, only savings through shorter trips. If individuals take long trips to eat out, then restaurants are imperfect substitutes and gains from variety are correspondingly large. Therefore, the key feature of the data for estimating this model is the decline in the probability of observing trips as their length increases. In practice, the shape of this decline is robust across types of individuals (e.g. income or age groups) and types of restaurant trips (e.g. week day trips, non rush hour trips, trips with only household members, trips whose only purpose is visiting a restaurant, etc). To obtain welfare estimates, I derive a variety-adjusted restaurant price index from the logit model.[5] In the simplest specification of the model, all the price variation among restaurants comes from differences in transport costs, and the restaurant price index in a location is low if there are many restaurants nearby, or if travel speed is high.

Estimating a discrete-choice model for travel destinations requires not only data on travel behavior, but also comprehensive microgeographic data on the location of all destinations available to an individual. The travel data comes from the National Household Travel Survey (NHTS), which identifies trips to a restaurant and the location of an individual's home at the block group level. Importantly, the NHTS allows to restrict the sample to trips with known origin whose only purpose is visiting a restaurant. The NHTS also allows the estimation of car travel speed in different areas. The restaurant data comes from Google's local business pages. The data contains information on the exact location of almost all restaurants (273,000 units) in 14 states representing 50% of the US population. For robustness tests and extensions of the model, I also collect data on restaurant characteristics. Restaurants' name and type of cuisine (e.g. 'pizza') come from their Google page, and for a subset of the sample there is additional information, such as meal price and quality ratings, from the popular review website Yelp.com.

The welfare estimation uncovers substantial variation across areas in the variety-adjusted restaurant price index, generating large spatial welfare differentials. The gains from density

[5] This index turns out to be identical to the 'love-of-variety' constant elasticity of substitution (CES) price aggregator. Anderson, de Palma, and Thisse (1992) prove that the under a linear utility specification, which I use, the logit and CES model lead to the same choice probabilities.

are very localized, and much of the variation in the price index occurs within metropolitan areas (MSAs).[6] For a car driver - I also compute indices for pedestrians - in a large MSA, the restaurant price index generally drops by more than 20% from an MSA's outskirts to its downtown, which represents yearly gains of about $600 for an average household. Generally less than 40% of these gains from density comes from shorter trip times, with the remainder accruing through gains from variety. In the countryside, individuals generally travel to one of the few restaurants that are closest to home, while in the densest areas travelers often pass by hundreds of restaurants on their way to a favorite destination. These results have important policy implications, because they allow us to anticipate the impact of policies promoting denser, walkable, mixed-used neighborhoods, that are arguably the most popular set of urban policies in recent years.[7] Such policies do reduce travel times, but ultimately have a larger effect on increasing gains from variety.[8]

A comparison of these results with recent estimates of the gains from variety in tradable goods hint at the primacy of non-tradable variety in explaining the consumption advantage of dense urban areas.[9] Handbury and Weinstein (2014) and Hottman (2016) use highly detailed retailer level Nielsen scanner data to show that residents of larger MSAs face a lower retail price index. I do not compute MSA level price indices, because my goal is to measure the gains from urban density, which turn out to be highly localized. Using consumer level data instead of only retailer level data demonstrates that most restaurants in a large MSA are essentially irrelevant to the welfare of any given resident, because of high travel costs. Keeping in mind this obstacle to a direct comparison, the substantial gains from variety in the service

[6]These findings are consistent with Albouy and Lue's (2011) quality-of-life estimates, which are higher in denser areas and vary almost as much within metropolitan areas as across them.

[7]Since the mid-1990s, the United States department of Housing and Urban Development has invested billions of dollar into such policies, that are usually inspired by New Urbanism, an influential planning movement (see Congress of the New Urbanism (2013)). For instance, New Urbanism theories are a major influence behind HOPE VI, which is HUD's program to revitalize distressed areas (Popkin, Katz, Cunningham, Brown, Gustafson, and Turner, 2004). From 1993 to 2010, HOPE VI made 263 grants worth $6.2 billions (`http://portal.hud.gov/hudportal/HUD?src=/program_offices/public_indian_housing/programs/ph/hope6`, webpage last visited in October 2013).

[8]Note that increasing density has a larger effect on reducing travel distance than travel time, because it lowers travel speed. Individuals, however, take more restaurant trips in dense areas.

[9]Murphy (2013) suggests that access to a high density of non-tradables enables individuals to save on land and durable goods (e.g. a car and a washing machine become unnecessary). According to this theory, the gains from non-tradable density are even larger than what I document here.

sector that I estimate are consistent with the key finding in Hottman (2016) that gains from variety in the retail sector come mostly from store variety, as opposed to goods variety. These results are consistent with the dramatic decline in the cost of shipping tradable goods over the last century, without a reduction of corresponding magnitude in the cost of moving people (Glaeser and Kohlhase, 2004). Urban density facilitates the movement of people, on which much of the non-tradable sector depends.

These welfare estimates are subject to a number of econometric and specification issues. First, restaurant characteristics may vary across areas with different density. For instance low density areas feature more pizza, burger and family restaurants. To address these issues, I estimate a nested-logit model in which restaurants serving the same type of cuisine are more substitutable. I also estimate specifications in which restaurants in the same chain are perfect substitutes. Average meal price and quality may also vary systematically with density, but partial price and quality ratings data from Yelp only show a small correlation for meal price and none for ratings. Comparing the price of a McDonald's Big Mac - a price index popularized by The Economist - across areas does not suggest enough spatial variation to qualitatively affect my results.

Second, individuals may sort into areas based on unobservable characteristics affecting their gains from density. For instance, individuals with higher value of travel time or higher taste for variety may prefer to live in denser areas. One can assess the strength of this sorting by comparing the effect of restaurant density on trip time in OLS regression to its effect in IV regressions. The instrument for restaurant density is past growth in population density, which has a large effect on current restaurant density after controlling for population in the initial period. The identification strategy is to restrict the sample to individuals with a very low probability of moving in any given year (55 years and older, married homeowner). For these individuals, recent population growth is an almost exogenous event, because a vast majority of them have lived in the same area for many years. OLS regressions predict shorter trip times in denser areas than IV regressions, suggesting that individuals with a higher value of travel time, who make shorter trips, sort into dense areas. Based on these results, I estimate a version of the logit model in which high-value-of-time individuals sort into high density areas.

Third, there may be joint sorting of individuals and restaurants. For instance, Waldfogel (2008) shows that the availability of different restaurant types depends on the characteristics of the local population. To address this issue, I specify a restaurant supply model that delivers a formula for the relative tastes for each type of cuisine in each area, which is equivalent to a quality parameter in a nested-logit model.

Finally, the model may be misspecified. In particular, the independence of irrelevant alternative (IIA) property imposes a strong restriction on the logit model. I show how to test the logit model's predictions, and the IIA, using regressions of trip time on measures of restaurant density. The logit model performs remarkably well, but regression analysis nevertheless identifies a discrepancy between the data and the model's prediction. The extensions of the logit model described above provide predictions closer to the data and generate similar welfare gains from density.

2. Literature review

The paper relates to an influential literature initiated by Rosen (1979) and Roback (1982), which uses data on wages and house prices to value city amenities. Albouy (2008) is a recent study using this approach. These studies estimate the value of urban amenities indirectly, as part of a larger residual explaining lower wages or higher house prices in a spatial equilibrium model. Therefore, the Rosen-Roback approach cannot determine willingness to pay for a particular amenity. This paper solves this measurement problem by using a different methodology, exploiting data on individual travel decisions to obtain direct estimates, at a precise location, of the value of a consumption amenity.

The use of travel cost differentials to value an amenity has a distinguished history in environmental economics, starting with Hotelling's (1947) letter to the National Park Service. Clawson (1959) provides the first of many applications of a travel costs method to the valuation of recreational facilities and environmental resources, which lack variation in prices from which demand curves are usually estimated. Ben-Akiva and Lerman (1985) develop the idea that travel demand can be modeled as a discrete choice problem.

A few recent papers also use data on restaurants or bars to investigate the importance of urban consumption amenities using different methodologies. Cosman (2015)'s evidence from entry and exit of firms in the Chicago nightlife industry supports the idea that consumers have a strong taste for visiting a variety of establishments. Kuang (2015) finds that restaurant accessibility is capitalized into higher house prices, and that this increase is larger for restaurants with favorable Yelp reviews. Davis, Dingel, Monras, and Morales (2016) results confirm that individuals take fewer trips to restaurants far away for their home or work location (spatial frictions), and push the consumer city literature in a new direction by documenting racial segregation in consumption choices over and above residential segregation (spatial friction).

Finally, the paper also relates to two major strands of literature in urban planning and transportation. First, the variety-adjusted price index for destinations that I estimate for restaurants corresponds to what transportation researchers call a 'travel accessibility index.' Bhat, Handy, Kockelman, Mahmassani, Chen, and Weston (2002) provide a literature review. Unlike available travel accessibility indices, the index proposed here has a natural interpretation as a price, and it depends on standard structural preference parameters. Second, reduced-form regressions of trip time on measures of restaurant density that I run to test the model belong to a large empirical literature measuring the relationship between travel and the built environment. The motivation behind these studies is generally to test whether higher population density living reduces vehicle travel, as argued by planning theories that influence much of recent urban policy. Ewing and Cervero (2010) provide a meta-analysis. Consistent with the regression results presented here, other studies find a relatively small effect of density on vehicle travel. The paper's contribution to this literature is to explain how this empirical regularity arises from a trade off between gains from variety and gains from shorter trips.

3. A logit model of travel demand

The analysis starts from two assumptions about the demand for travel. The first is that destinations are substitutable, which implies that an individual prefers some destinations to others. The second is that travel is costly, so that the price of visiting a destination farther away is higher. These assumptions imply a trade-off between the gains from going to a preferred destination and the costs of a longer drive.

I model the decision problem of an individual who first chooses how much to spend on a composite restaurant good versus all other goods, and then chooses which restaurant to visit. To solve this problem, I work backwards and begin by studying the decision of an individual living at location k and choosing a restaurant. Let i index the number I_k of restaurants available, so that $i \in \{1,2,3,\ldots,I_k\}$. The restaurant with index i = 1 is closest from location k, i = 2 is second closest and so on. Denote travel time to restaurant i by t_{ki} and fuel cost by f_{ki}. The price of a meal at any restaurant is a constant p. The total price of eating at restaurant i, including transport costs to and from the restaurant, is $p_{ki} = p + 2(\gamma t_{ki} + f_{ki})$, where γ is the value of travel time. This total price is what should be understood when referring to restaurant price elsewhere in the paper, unless 'meal' price is mentioned specifically. Each restaurant receives a random idiosyncratic shock ϵ_{ki}, which captures an individual's preference for restaurant i. ϵ_{ki} is a random draw from a type I extreme value distribution. Note that parameters of the model do not vary with individual characteristics like income, which I introduce later in robustness checks and extensions of the model.

Define the utility from visiting restaurant i as:

$$u_{ki} = (1-\sigma)ln(p_{ki}) + \epsilon_{ki}.$$

The individual's problem is to choose the restaurant i that maximizes her utility:

$$max\{(1-\sigma)ln(p_{k1}) + \epsilon_{k1}, \ldots, (1-\sigma)ln(p_{ki}) + \epsilon_{ki}, \ldots, (1-\sigma)ln(p_{kI_k}) + \epsilon_{kI_k}\}. \tag{1}$$

The logit choice probability is equal to $\frac{e^{(1-\sigma)ln(p_{ki})}}{\sum_{i=1}^{I_k} e^{(1-\sigma)ln(p_{ki})}} = \frac{p_{ki}^{1-\sigma_j}}{\sum_{i=1}^{I_k} p_{ki}^{1-\sigma}}$, for all restaurants i (see Train (2009) for details and a proof.)

While this specification can be estimated and used to derive a price index, one additional assumption allows the recovery of exactly the same aggregate consumption shares and welfare gains as one would obtain from a standard CES love-of-variety model. Assume that individuals have a fixed restaurant budget y_k (which can vary by area k), so that people choosing a cheap restaurant make more frequent visits q_{ki} to that restaurant, i.e. $y_k = q_{ki}p_{ki}$. This constraint has little impact on the welfare results, because of the large values of σ estimated in practice.[10] With this budget constraint, the probability of a trip of length t_{ki} to restaurant i, given the set of travel times to all restaurants $T_k = \{t_{k1}, \ldots, t_{ki}, \ldots, t_{kI_k}\}$ and the set of fuel costs $F_k = \{f_{k1}, \ldots, f_{ki}, \ldots, f_{kI_k}\}$, becomes:

$$prob_{ki} = prob(t_{ki}|T_k, F_k) = \frac{p_{ki}^{-\sigma_j}}{\sum_{i=1}^{I_k} p_{ki}^{-\sigma}}. \tag{2}$$

An important property of the probability in equation (2) is that it can be estimated using variation in price coming from travel time and fuel cost data for restaurant trips, without requiring information on exact restaurant choice. To better understand the workings of the model, consider the probability ratio of trips to restaurants 1 and 2 (the closest and second closest restaurants):

$$\frac{prob_{k1}}{prob_{k2}} = \left(\frac{p_{k1}}{p_{k2}}\right)^{-\sigma_j} = \left(\frac{p + 2(\gamma t_{k1} + f_{k1})}{p + 2(\gamma t_{k2} + f_{k2})}\right)^{-\sigma}. \tag{3}$$

Equation (3) highlights two key features of the model. First, if σ is high, then restaurants are very substitutable and the ratio in equation (3) is large. When σ is high, individuals are sensitive to price differences, so they travel mostly to the closest restaurant, which is cheaper because of lower travel costs. This will be the main intuition behind the strategy for estimating σ using travel data. Second, if the difference between t_{k1} and t_{k2} is large, in a low-density area in which restaurants are far apart, then the proportion of trips to the closest restaurant is also large. Individuals living in low-density areas mostly visit the closest restaurant instead of traveling to places that they prefer, because substituting between restaurants is expensive. Therefore, higher density allows individuals to cheaply substitute between destinations, and to visit places that they prefer.

Equation (3) also shows that σ represents the elasticity of substitution between restaurants.[11] This elasticity has two interpretations. In the first interpretation, individuals have constant tastes and always travel to the same restaurant, as in the model. In this case, a

[10] Whether this assumption is a better fit for the data is impossible to verify with daily data. Note also that it is easy to specify a model in which q_{ki} is a primitive of the utility function (see Sheu, 2014).

[11] The elasticity of substitution in this setting is a parameter measuring, for any two restaurants, the ratio of percentage change in relative demand to percentage change in relative prices. For instance, a low elasticity of substitution means that demand is not responsive to price variation.

low σ represents heterogeneous preferences for restaurants across many otherwise identical individuals. In the second interpretation, individuals get new idiosyncratic shocks from the same distribution before each restaurant choice. In this case, a low σ represents a taste for variety. The price index in the next section does not distinguish between these two interpretations, and neither do the empirical results.

3.1 *A price index*

This subsection discusses price indices able to measure the gains from density across locations. It is easy to derive the following well-known relative price index from the logit model above:

$$R_{k,k'} = \frac{\left(\sum_{i=1}^{I_{k'}} p_{k'i}^{1-\sigma}\right)^{1/(1-\sigma)}}{\left(\sum_{i=1}^{I_k} p_{ki}^{1-\sigma}\right)^{1/(1-\sigma)}}. \tag{4}$$

$R_{k,k'}$ is the factor by which restaurant prices in area k would have to change in order to equalize utility in area k and k'. It is exactly the relative price index that would be derived from CES preferences, a result first shown by Anderson *et al.* (1992).[12]

It is useful to define the numerator in equation (4) as a variety-adjusted price index in area k, denoted by R_k, and the denominator as a variety-adjusted price index in area k', denoted by $R_{k'}$, so that for instance:[13]

$$R_k = \left(\sum_{i=1}^{I_k} (p + 2(\gamma t_{ki} + f_{ki}))^{1-\sigma}\right)^{1/(1-\sigma)}. \tag{5}$$

[12]I do not use the exact price index proposed by (Sato (1976) and Vartia (1976)) for CES preferences, or the equivalent index that is robust to the introduction of new goods, introduced by Feenstra (1994). These indices are useful because they provide expressions in which the expenditure share on each variety captures an unobserved quality parameter, which disappears from the expression of the exact price index. In my framework, however, the particular quality parameter of any given restaurant is less relevant, because variation in prices come from variation in transport costs, not from unobserved quality. I include such a quality parameter, that I estimate directly for each types of cuisine, in the nested-logit model of section 7.2.

[13]This price index also has an interesting interpretation as what transportation researchers call a 'travel accessibility index'. Ben-Akiva and Lerman (1985) propose to use the denominator of a logit probability in a travel demand model as a travel accessibility index, and Niemeier (1997) is the first to estimate such an index in a model of mode choice and commute to different types of job. The index in Equation (4) is easy to interpret because it comes from a linear utility specification of Anderson *et al.* (1992) that introduces value of travel time as a structural parameter.

3.2 *Expenditures on restaurants versus all other goods*

Results comparing R_k across areas are the focus of this paper, but it is also instructive to compute welfare gains in monetary units. To do so, the relative price index must account for the degree of substitution between restaurants and all other goods, and for the possibility that expenditures on restaurants are higher in locations with a lower restaurant price index. To provide such an index, I solve a nested-logit model with one nest for restaurants - the choice of a restaurant within this nest is solved for above - and one nest for all other goods. Suppose that G_k is a price index for all other goods in location k. Then the aggregate relative price index is:

$$P_{k,k'} = \frac{(R_{k'}^{1-\nu} + G_{k'}^{1-\nu})^{1/(1-\nu)}}{(R_k^{1-\nu} + G_k^{1-\nu})^{1/(1-\nu)}}, \tag{6}$$

where R_k is given by equation 5 and ν is the elasticity of substitution between restaurants and all other goods. This index obtained from a nested-logit model is exactly that which would be obtained from a nested-CES model, a correspondence first established by Sheu (2014). Estimates of the parameter ν are available from the literature and its value turns out to have little impact on estimated welfare gains. The online appendix E confirms that consistent with this model, individual's probability of traveling to a restaurant decreases with the restaurant price index in their area.

3.3 *Maximum likelihood estimator for σ*

The elasticity of substitution σ is an unknown parameter, whose estimation is necessary to compute the gains from restaurant density. With data on multiple trips starting from the same location, one could estimate σ as the coefficient from an OLS regression of difference in log prices on difference in expenditure shares, for pairs of restaurants available from that location. In the dataset assembled in section 4, however, almost every trip originates from a different location, and no two locations offer an exactly similar set of available restaurants. I therefore propose a maximum likelihood estimator for σ that accounts for the exact restaurant choice set of each traveler. This simplest version of the estimator does not allow for variation in individual or restaurant characteristics.

Suppose that we have a sample of N trips to restaurants, indexed by n. Consider a trip of length t_{nk}, that originates in location k. From equation (2), one can write the predicted probability of that trip as a function of T_k, F_k and the parameter σ, so that:

$$prob(t_{nk}|\sigma,T_k,F_k) = \frac{(p + 2(\gamma t_{nk} + f_{nk}))^{-\sigma}}{\sum_{i=1}^{I_k}(p + 2(\gamma t_{ki} + f_{ki}))^{-\sigma}}.$$

The log-likelihood function is therefore:

$$\ell(\sigma,T_N,\mathbb{T}_K,\mathbb{F}_K) = \sum_{n=1}^{N} log(prob(t_{nk}|\sigma,T_k,F_k)),$$

where T_N denotes the set of all trip lengths in the sample, $\mathbb{T}_K$ denotes the set of all sets T_k and $\mathbb{F}_K$ denotes the set of all sets F_k. The maximum likelihood estimate is the value of σ that maximizes the sum of log probability of observing each trip length in the sample:

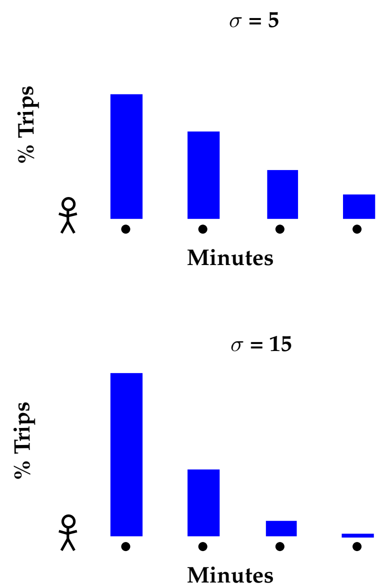
$$\hat{\sigma} = \underset{\sigma}{\text{argmax}}\ \ell(\sigma,T_N,\mathbb{T}_K,\mathbb{F}_K). \tag{7}$$

Figure 1 illustrates how the distribution of observed trip lengths identifies σ in the model. All distances in the figure are in units of time, and each dot represents a restaurant available to an individual. The blue bar above each restaurant is the model's predicted probability of a trip to that restaurant. In the bottom diagram, σ is high at 15, so demand is very responsive to variation in prices due to transport costs. As a result, the model predicts that the probability of a trip to the closest restaurant is much larger than that to restaurants far away. Therefore, the estimator generates a high σ if the data features a large share of trips to the closest restaurant(s), in all locations. This pattern implies small gains from variety, because individuals are unwilling to incur transport cost to access a place that they prefer.

The elasticity of substitution σ determines the importance of gains from variety, but the model also allows the measurement of gains from shorter trips. Figure 2 offers a simple example of how gains from shorter trips arise in the model. The same σ is used to obtain predictions in both diagrams, and the proportion of trips to each restaurant is (almost) the same. The individual in the bottom diagram, however, takes on average longer trips, because she lives farther from the entire set of restaurants available.[14] This prediction is

[14]The model predicts that an individual living in a suburb five minutes away from the nearest restaurant drives on average approximately five minutes less on his trip than another individual living farther out, 10 minutes away from the same distribution of restaurants. Proposition 3 in Section B of the online appendix provides a formal statement and a proof.

Figure 1: What identifies σ

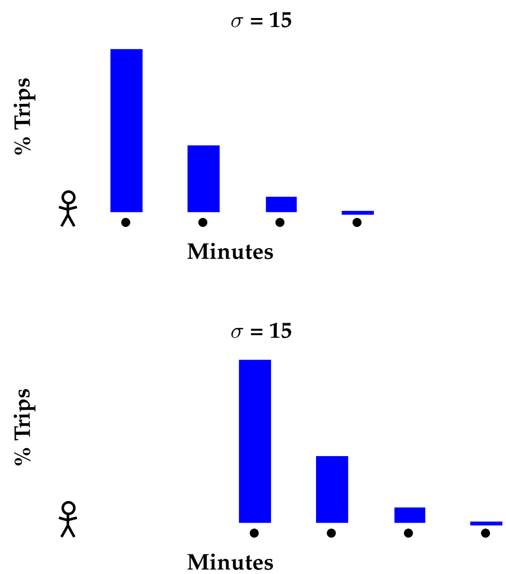


especially relevant given that a majority of Americans live in residential areas, relatively far from commercial zones.

3.4 *Identification, misspecfication, sorting and sensitivity analysis*

Identification In general, insensitivity to price variation indicates a preference for higher quality products, not a taste for variety. The key advantage of the estimation method proposed above is that price variation identifying σ originates from travel costs that are plausibly unrelated to unobserved restaurant characteristics that affect prices, like quality. Therefore, the main identification challenge to an estimation strategy relying on willingness to travel is systematic differences between restaurants that are on average close to travelers and restaurants that are on average far. Such systematic differences are unlikely to arise, because the same restaurant which is located 5 minutes away from an individual is also 10 minutes away from another individual living elsewhere. Section 7 uses data from Yelp.com to show that such differences between restaurants on average close and restaurants on average far from travelers are indeed small. Section 7 also provides an upper bound for the small bias due to ignoring this type of price/quality variation, by computing welfare estimates that let meal price vary with travel distance with no compensating quality variation. Note that formally,

Figure 2: Where do gains from shorter trips come from?



the assumption of a constant meal price elsewhere in the paper is equivalent to assuming that utility is invariant to variation in meal prices, because higher prices are always exactly compensated by higher quality. This is a reasonable starting point if quality is imperfectly measured and mostly produced through variable costs, as is likely the case in the restaurant industry (Berry and Waldfogel, 2010).[15]

Another identification concern is joint sorting of restaurants and individuals, in particular the possibility that individuals choose to live close to their preferred restaurant types, and take shorter trips as a result of these unobservable tastes. In this case σ is biased upward and the gains from variety are underestimated. The solution proposed in Section 7 is to solve the supply side of a restaurant choice model, which allows the derivation of area-specific tastes for various cuisines from the local restaurant supply of cuisines.[16]

[15]In a complementary analysis, Kuang (2015) finds that high Yelp restaurant ratings increase the price of nearby houses, controlling for Yelp restaurant prices. Although individuals likely adjust their Yelp rating to account for the price that they paid (e.g. 'good food but not worth the price'), Kuang (2015) results highlight that prices are of course not always proportional to quality. However, this need not create a systematic bias given an identification strategy based on travel costs.

[16]Note that this exercise does not require the specification of a residential choice model. Such a model would illuminate the trade-off between high house prices and low amenity price indices, through which the willingness to pay for consumption amenities that I estimate is capitalized into house prices. This analysis is outside of the scope of this paper and left for future work (see Kuang (2015) for a reduced-form analysis).

Misspecification An important restriction on the logit model is the independence of irrelevant alternative property. It is important to understand how this property affects estimation results, and to show that it is testable. Intuitively, the IIA means that restaurants are infinitely differentiated, and destinations far from home are never 'similar' to other options closer from home. More precisely, it means that the relative demand for two restaurants depends only on their relative prices, and not on the price of any other restaurants. One important implication of this property is that a uniform increase in density has no effect on average trip length, because it maintains the proportion of trips of each length constant. When estimating the model, this implies that variation in trip lengths across (uniform) density levels does not contribute to identifying σ. When testing the model, the prediction that a uniform increase in density does not increase trip time means that regressions of density on travel time from Section 7 are tests of the IIA property of the logit model.[17]

Sorting and heterogeneity One can easily extend the logit model to account for restaurants and individuals' heterogeneity and sorting across density levels. These extensions refine welfare estimates beyond gains from additional restaurant density. For instance, one can measure willingness to pay for greater dispersion in types of cuisine, or evaluate whether gains from density accrue to particular income groups. It is important to emphasize, however, that sorting does not explain the decline in the likelihood of trips as their lengths increase, and therefore does not create obvious biases in estimating σ. As a result, models allowing for individual and restaurant heterogeneity deliver estimates of the gains from density very similar to those obtained from the basic logit model, as Section 7 will show.

One natural way to add observable restaurant characteristics to the model is to allow restaurants in the same chain to be perfectly substitutable, or restaurants serving the same type of cuisine to be more substitutable. These simple extensions alleviate concerns that dense areas feature more variety of cuisines and fewer chains, relax the IIA property of the

[17]Proposition 2 in the online appendix provides a proof. Note that if the IIA does not hold, say because all burger restaurants are similar, then one should observe shorter trip lengths at higher density. The reason is that a high density area almost certainly features a burger place among the dozens of restaurants very close from home, removing the need to travel far for a burger. The IIA property of the logit and CES models is the object of valid criticism, for instance by Ackerberg and Rysman (2005), but ultimately its relevance is an empirical issue.

logit model to address potential misspecification issues, and can be adapted to account for how supply of cuisines reflects local tastes. Without data on restaurant choice, the estimation of models with restaurant characteristics is necessarily indirect, so they do not provide the preferred estimates in this paper, but instead confirm the welfare estimates from the basic logit model. There is no direct way to handle unobservable restaurant heterogeneity in this context, but one should note that average restaurant prices, quality ratings and other observable characteristics feature only moderate variation across density levels.

To investigate the impact of observable individual heterogeneity on the welfare results, I estimate σ and the welfare gains from density separately by income groups in online appendix D, as well as a model in which travel speed and fuel costs vary with individual characteristics like age, income, education and vehicle type. To investigate the impact of unobservable individual heterogeneity, I propose an instrumental variable strategy that assesses the importance of sorting on unobservables (σ and γ) across restaurant density levels. I find evidence of sorting by value of time, so I modify the maximum likelihood estimator to let γ vary with restaurant density. [18]

Sensitivity to parameter values Welfare estimates could be sensitive to the choice of value of travel time γ, a well-studied parameter that I do not estimate.[19] Section C of the online appendix provides a sensitivity analysis showing how changes in parameters' value affect the welfare estimates. Welfare gains remain within the same order of magnitude even following large perturbation like doubling γ or reducing it by half.

[18] One source of bias comes from drivers who undertake long trips to meet friends in a given restaurant, or to accommodate family members on the trip who have different preferences. First note that trips whose main purpose is to socialize with friends are separately identified in the data described in the next section, and should not be in the restaurant trip sample. In the reduced-form analysis of section 7, I control for many trips and individual characteristics and find that each additional adult on a trip adds 8% to trip length, and each children about 3%. Whether the passenger is a household member or not does not matter. To the extent that families eating out together are less likely to join friends at the destination, then travel to meet friends does not explain the long trips observed in the data. The relatively small effect of additional passengers on trip time - some of which can be due to sharing fuel costs - also suggest that the logit model, in which one decision maker ignores the preferences of other passengers, provides a reasonable approximation of reality. Moreover, estimates of σ vary little when estimating the model under the assumption that two or more decisions-makers with exactly the same preferences make a joint travel decision.

[19] The source of variation that identifies σ (variation in trip length) is similar to that which could identify γ. So I focus on providing the first estimate of σ in the service sector, and rely on a large literature estimating γ, generally from data particularly suited to this task.

Similarly, one could worry that studies estimating the parameter ν – which capture the substitution between restaurants and all other goods and enters the formula delivering a monetary value of the welfare gains from density – do not account for the possibility that individuals living in high restaurant density areas have a preference for restaurant expenditures.[20] Again, results in Appendix A show that welfare estimates are not sensitive to large variation in ν, but rather depend crucially on total restaurant expenditures and on the restaurant price index, the measurement of which is the focus of this paper.

4. Data

Estimating the logit model requires data on the location of a traveler, on the length of her trip to a restaurant, and on travel time and fuel costs to each restaurant available to her. The data on restaurant location come from the Google Places page of each restaurant in the summer of 2011 (these pages are currently called Google+ Local pages). The travel data, which identify trips to a restaurant, are from the 2008–2009 edition of the National Household Travel Survey (NHTS).

4.1 Restaurant data

Data from Google Maps applications offer complete coverage and exact information on restaurant location, both necessary for the innovations of the paper. As an aggregator of local business data, Google Places includes a page for any restaurant with a presence on alternative websites such as Yellow Pages, or an owner willing to create its own page. I collect data on all restaurants in a set of 14 US states, containing more than 50% of the US population. I select these states because each of them funded the collection of additional data in my travel

[20]Results in online appendix E shows that the price index at home has a large impact on the number of trips from home and a much smaller impact on all other trips, suggesting that such sorting plays a limited role. This endogeneity problem resembles that considered in Dubin and McFadden (1984), who note that electricity usage and appliance choice may share a common error term, or Goldberg (1998) who studies car usage and vehicle choice.

database, beyond the federally funded national sample.[21] The restaurant sample consists of 273,000 eating places.[22] The data includes fast food and full-service restaurants, as well as pubs, delis and other eating places. Coffee shops, such as Starbucks, are almost entirely excluded.

For robustness tests and extensions of the model, I also collect data on restaurant characteristics. The Google Places page of a restaurant provides the name of the restaurant and the type of cuisine that it serves (e.g. Korean, American, chicken, sushi). I code restaurants into 85 such categories, using definitions from Yelp.com, the most popular user review website for restaurants. I also identify restaurants belonging to the 50 largest restaurant chains in my sample, the largest of which is Subway. At the time of data collection, about 50% of Google Places pages contained a hyperlink leading to an alternative restaurant page on Yelp. Yelp contains information on average quality ratings from private reviewers (from 0 to 5 stars in 0.5 increments), prices ($, $$, $$$ and $$$$, coded as $7, $17, $40 and $80),[23] number of reviews, and sometimes on attire, ambience, parking availability, and whether a reservation is necessary. A conflict between Google and Yelp occurred about a third of the way through data collection, after which Google removed the link to Yelp from its pages. As a result, Yelp data is only available for 70,000 restaurants, concentrated in the largest metropolitan areas due both to the data collection strategy and to the geographical preferences of Yelp's contributors.

4.2 Travel data

The NHTS is a nationally representative survey of travel behavior conducted about every six years. State transportation agencies can fund the collection of additional (add-on) travel data, which are also publicly available. The sample is restricted to 125,000 households in these

[21] The states in my sample are Arizona, California, Florida, Georgia, Indiana, Iowa, New York, North Carolina, South Carolina, South Dakota, Tennessee, Texas, Vermont and Virginia. I add Arizona, which purchased two regional-level add-on data, but no state-level add-on, and exclude Wisconsin, that purchased a state-level add-on which lacks geographical coverage. The states that I exclude do not have enough travel data to compute estimates of car speed at the local level, and too few trips to justify restaurant data collection.

[22] Within these states, the National Restaurant Association estimates the number of 'eating and drinking' places at 269,000, suggesting that my sample is comprehensive. The NRA's state-level reports are accessible at `http://www.restaurant.org/research/state/`. I also have a partial sample of 168,000 restaurants in other states of the country (for a total of 440,000 restaurants) to reduce measurement error from trips across state borders.

[23] On Yelp, the dollar signs represent the 'approximate cost per person for a meal including one drink, tax and tip': $ = under $10, $$ = $11-30, $$$ = $31-60, $$$$ = above $61.

add-on states, representing 90% of the NHTS total. Each participating household member completes a travel diary on a travel day assigned to the household, recording the purpose, length, duration, start time and mode of every trip undertaken that day. Crucially, the data identify trips to 'get/eat meal', the origin of the trips (e.g. home) and the purpose of the next trip (e.g. return home). The data also contain a rich set of individual, household, and trip characteristics, as well as confidential information on the block group in which an individual resides. Trips to or from a restaurant represent about 11% of all trips, and about 25% of households have at least one member going to a restaurant on their travel day. The median trip to a restaurant is about 3 miles and lasts 10 minutes, with higher averages at 6 miles, and 14.5 minutes. About 90% of trips to a restaurant are by privately-operated vehicle ('car', for short) with almost all the remainder by foot.[24]

4.3 Sample selection

The travel data contains enough information to restrict the trip level estimation sample to a set of comparable trips with known origin whose only purpose is traveling to a restaurant.

I first restrict the sample to trips by car, which are more comparable (there is evidence, for instance, that walkers have a higher value of travel time). However, I will also compute price indices for pedestrians, using the σ that I estimate for car drivers. I eliminate the small percentage of car trips taken in high-density census tracts in which more than 20% of trips are by foot, because individuals in these areas may choose the car only for long trips, and walk for shorter trips.

About 40% of all trips to a restaurant start from home, and for the empirical analysis I restrict the sample to these trips, whose geographical origin is known at the block group level.[25] Importantly, the NHTS also allows me to restrict the sample to trips that are immediately

[24]Results sometimes differ depending on whether NHTS sampling weights are used. These weights account for the oversampling of some categories of individuals (e.g. older) in the NHTS. While most numbers are similar in both cases, the unweighted percentage of car trips is 92.5% while the weighted percentage is 88.3%.

[25]Block groups are small, which alleviates concerns about measurement error on the location of a traveler. The median radius of block groups is approximately 0.4 miles. I assume that each traveler resides at his block group's population-weighted centroid, which I obtain from the Missouri Data Center's MABLE Geocorr2K database. MABLE Geocorr2K computes a block group's centroid from the centroids of each of its constituent census blocks, using census block populations as weights.

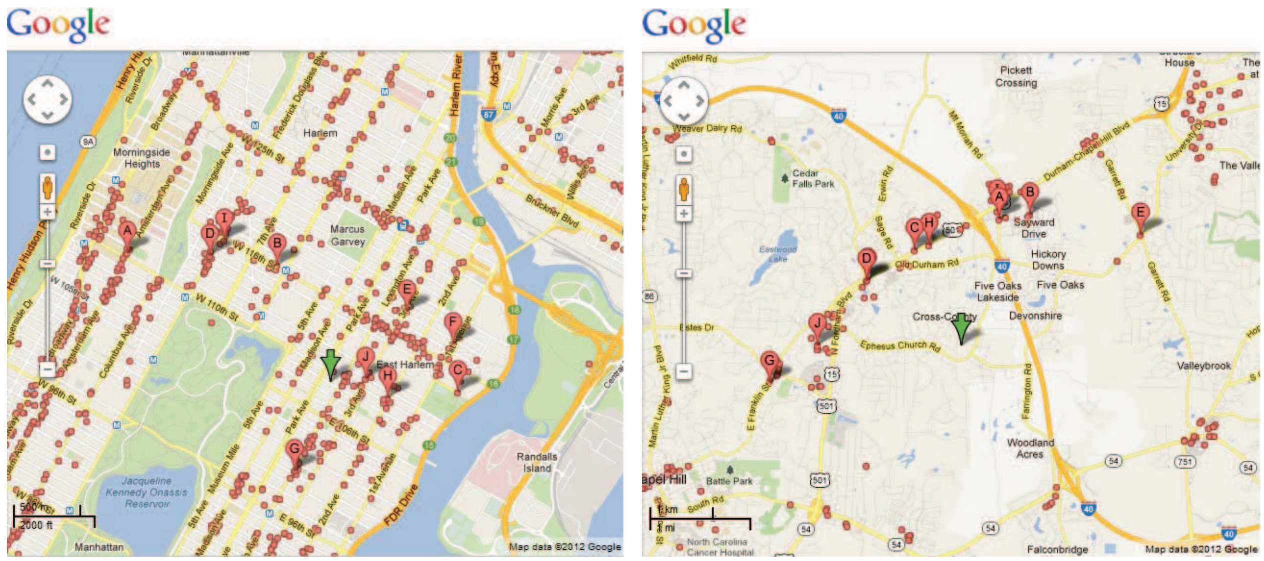
followed by a trip back home. When a trip from home is followed by a trip to a destination other than home, the benefits from reaching that next destination (e.g. a movie theater) also affect the travel decision. In these cases, which account for 33% of trips from home, observing long trips does not necessarily imply a high willingness to incur travel costs to visit preferred restaurants.

I eliminate trips longer than 45 minutes, because estimating the model requires limiting the size of the restaurant choice set in each location. Capping the sample at 30 or 60 minutes has little effect on the estimates, because individuals rarely take very long trips to a restaurant (45 minutes corresponds to the 98^{th} percentile of trip time.) Finally, I remove multiple observations of the same trip for different household members, and keep only the driver's trip. To summarize, the trip level estimation sample consists of 7,409 trips to a restaurant shorter than 45 minutes, from home and immediately back, by a driver. In Section C of the online appendix, I estimate the model using different trip samples to show that although sample selection can remove biases in the expected direction, it has no sizable impact on welfare estimates.

4.4 Assembling the data

Estimating the model requires computing, for each traveler, the travel time and fuel cost to each restaurant in her choice set. The two Google Maps in Figure 3 illustrate the matching between a traveler and her restaurant choice set. On each map, a downward-pointing arrow indicates an individual's residence, at her block group population-weighted centroid. Each circle represents the location of a restaurant (the alphabetical markers are Google's recommendations). The choice set of a traveler consists of all restaurants available within 45 minutes of travel.

Estimates of travel costs must account for the fact that travel time between any two equidistant locations is much slower in Manhattan than in a suburb of Chapel Hill. To compute travel times from an individual to a restaurant, I first calculate the linear distance between the geographical coordinates of an individual's home and that of the restaurant. I then multiply this linear distance by a correction factor of 1.67, because the driving distance between any



(A) A high-density urban area: East Harlem, Manhattan, New York City, NY (Maps data @2012 Google)

(B) A medium-density suburb in Chapel Hill, NC (Maps data @2012 Google)

Figure 3: Google Maps with restaurants

Notes: Each panel contains a screen-shot from Google Maps resulting from the search command 'Restaurants near [geographical location]'. The downward-pointing arrow indicates the location of an individual's population-weighted block group centroid. Each circle represents the location of a restaurant. The markers from A to G are Google's restaurant recommendations for the search. The scale of the map is at the bottom left. The map in panel B is at twice the scale of that in panel A. Google Maps is available at: `http://maps.google.com/`

two points is longer than the length of the shortest path connecting these points.[26] Travel time, in minutes, is equal to distance times speed. I obtain measures of car travel speed for each trip using fitted values from regressions on the entire NHTS sample of car trips. In these regressions, speed varies with the census tract an individual lives in, with travel distance to the restaurant, and in some estimations with the characteristics of an individual (age, education, income, etc). The details of these regressions are in Appendix B.

Fuel costs depend on travel distance and speed, and in some estimations on the vehicle type of a traveler and on the price of gasoline in a location on a given day. The details of fuel cost construction is in Appendix B.

[26] I use a Google Maps application programming interface called Google Distance Matrix to obtain actual driving distance for a representative sample of individual/restaurant pairs (using only the 20 restaurants closest to an individual, which are most relevant). 1.67 is the average difference between the linear distance between two points and the driving distance from Google Distance Matrix. I do find some variation across areas and across trip length in that factor, but not enough to qualitatively affect my results, so I choose the constant factor for simplicity. It would be possible, but prohibitively costly, to use the application to compute driving distances (or time) from all individuals to all restaurants in my sample.

To assemble the final dataset used to estimate the model, I match each trip in the sample of 7409 trips to a restaurant with information (travel times and fuel costs) on all restaurants available within 45 minutes of the location from where the trip originates.

4.5 *Spatial distribution of restaurants*

Restaurants are far from being uniformly distributed in space, and a brief discussion of their spatial distribution illuminates many results in the paper. From the perspective of an individual traveler, the distribution of restaurants has two major characteristics. To varying degrees, these characteristics are apparent in the two maps from Figure 3. The individual in panel A lives in East Harlem, a high-density area in New York City. The individual in panel B lives in a medium-density suburban area of Chapel Hill, North Carolina. First, individuals live relatively far from the closest restaurant(s). Most Americans, like the individual in panel B, live in a residential suburb, at some distance from the nearest commercial outlets. Second, the number of restaurants available increases more than proportionally with distance (and time), and this increase is faster in denser areas. Both panels suggest that there are fewer restaurants available between 0–5 minutes of travel from home than between 5–10 minutes. This increase is stronger in a high-density area because restaurants locate on a dense network of major urban roads crossing each other in a two-dimensional plane. Low-density areas are closer to a one-dimensional world, in which restaurants locate on the town's sole major road. Therefore, a larger proportion of the mass of restaurants is located far from an individual in dense areas. This feature of the restaurant distribution is central to the interpretation of regressions on measures of restaurant density that I use to test the model in Section 7.

5. Estimation of the logit model of travel demand

The estimation sample consists of all trips to a restaurant by a driver that are shorter than 45 minutes, start from home, and are followed by a return trip home. Each of these trips is matched to the set of trip times and fuel costs to all restaurants that the traveler can visit within 45 minutes of travel. Data on observed trip time to restaurants is sufficient to estimate equation (7), as restaurants are only differentiated by transport costs from home, and by a random utility shock.[27] Meal price is set at a constant value of p =\$13. To set a value of travel time, I refer to Small and Verhoeff (2007), who review estimates of the value of driving time from a large literature, and suggest a value equal to 50% of a person's average hourly wage, which corresponds to \$12 per hour i.e. γ = 0.2.

The maximum likelihood estimate from equation (7), obtained by grid-search, is $\hat{\sigma} = 8.8$ (in column (1) of Table 1). A plot of the log-likelihood function suggests that it is concave for any reasonable values of σ, and therefore that $\hat{\sigma}$ is a global maximizer. Column (2) lets travel speed to each restaurant vary with individual characteristics like age and income, and fuel costs vary with vehicle type, and delivers the same $\hat{\sigma} = 8.8$. Letting speed vary with time of day (e.g. evening congestion) complicates data assembly but also leads to similar results.[28] This elasticity of substitution between restaurants is relatively large compared to existing estimates for consumer goods, but it is low enough to generate much extra travel beyond the closest restaurant, and as shown in section 6, substantial welfare gains. I am not aware of other estimates of the elasticity of substitution for services and non-tradables like restaurants.

5.1 *Can the logit model match the distribution of trip time in the data?*

As explained before, σ is identified from the distribution of trip time in the data. This section shows what this distribution looks like, and demonstrates the logit model's ability to match it. One can obtain a simulated trip time distribution by drawing a trip time for each driver in the sample using the probability distribution generated by the model at $\hat{\sigma} = 8.8$. The results of this comparison are in Figure 4, which shows that the proportion of trips within any given

[27]For about 15% of trips, observed trip time is shorter than my estimate of travel time to the closest restaurant, because of measurement error. In these cases, I assume that a traveler's location is such that trip time t_{nk} is exactly equal to travel time to the closest restaurant t_{k1}, and I add $t_{k1} - t_{nk}$ to the travel time of each restaurant in T_k. Such mistakes are generally small and occur for short trips to restaurants which are almost closest (e.g. someone enters a 5 minute trip - a round-up value - and I estimate that the closest restaurant is 5.5 minutes away). There are some larger discrepancies in low-density areas with large block groups and imprecise measurement of t_{k1}.

[28]I also estimate the model by weighted maximum likelihood, using NHTS sampling weight. These weights are equivalent to the number of individuals that each observation in the sample represents in the population, and account for over-sampling of some areas or type of households. I find $\hat{\sigma} = 9.2$.

Table 1: Maximum likelihood estimation of logit model of travel demand

	(1)	(2)	(3)	(4)	(5)	(7)
$\hat{\sigma}$	8.8	8.8	8.4	8.4	8.4	9.2
	(0.06)	(0.06)	(0.07)	(0.06)	(0.06)	(0.08)
$\hat{\beta}$			0.38			
			(0.02)			
$\hat{\mu}$						3.6
						(0.25)
Speed and fuel costs vary with individual char.		X				
Sorting by value of travel time			X			
Meal price varies with distance				X		
Perfect substitutability within chain					X	
Nested-logit (types of cuisine)						X
Observations	7409	6800	7409	7409	7409	7409

Notes: σ is the elasticity of substitution between restaurants, β captures the strength of sorting across density levels by value of travel time, and μ is the elasticity of substitution between different types of restaurant cuisine. Estimates obtained by grid-search in all columns. Standard errors in parentheses computed using the outer-product-of-the-gradient estimator, as suggested in Berndt, Hall, Hall and Hausman (1974).

time interval looks remarkably similar in simulated and actual data.[29] This decline in the probability of a trip as its distance increases is the key feature of the data that determines σ. Crucially, the shape of this decline is robust to controlling for individual or trip characteristics. For instance, one can easily estimate σ separately for a given income or age group, or for week day trips, non rush hour trips, trips with only household members, etc, and generate estimates of σ generally well within a 7 to 11 range.[30]

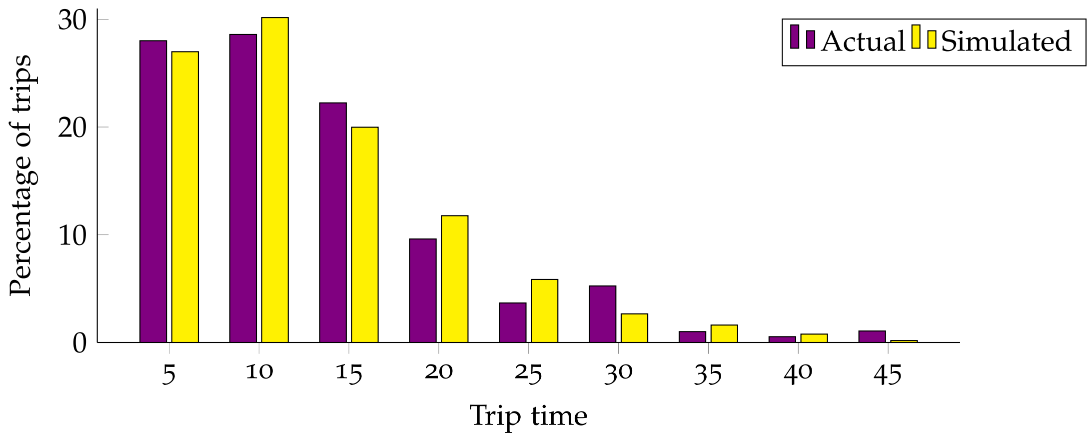
6. Welfare gains from density

This section present estimates of the welfare gains from restaurant density. I first compute the variety-adjusted restaurant price index in each block-group centroid in the sample, for both drivers and pedestrians. I then convert variation in the index into an average willingness

[29] The simulated data is obtained using the estimate of σ in column 1 of Table 1. The proportion of 5 minute trips is almost the same as that of more expensive 10 minute trips because many travelers do not have any restaurants available within 5 minutes of travel from home.

[30] Estimating σ by income groups is more involved because it requires to take into account rich peoples' higher value of time, so I present these computations in online appendix D. Online appendix C explores the sensitivity of the welfare estimates to changes in the parameter σ.

Figure 4: Distribution of trip times, actual and simulated data



Notes: Sample of 7409 restaurant trips by a driver, starting from home and followed by a return trip home. The y-axis represents a time interval around the values indicated. This interval is 0 to 7.5 minutes for 5 minutes trip, 42.5 to 45 minutes for 45 minutes trip, and otherwise $x - 2.5$ to $x + 2.5$ for a x minutes trip.

to pay for restaurant density. Finally, I use regression analysis to decompose the sources of the gains from density into shorter trips and gains from variety, and propose an alternative measure of the gains from restaurant density that does not rely on structural estimation of a model.

6.1 Welfare differences across areas

For each block group centroid in the sample, equation (5) delivers a variety-adjusted restaurant price index at the maximum likelihood estimate of σ from column (1) in table 1. I compute the index both for a driver and for a pedestrian. Public transportation is not an option is most of America, and its use for eating out is negligible.[31] The value of the price index at any given location decreases with the number of nearby restaurants, and with car travel speed. Table 2 contains percentiles of the price index for a driver and for a pedestrian, with examples of locations at each percentile. For a car traveler, the median restaurant price index is equal to 9.3, which is lower than the average price of a restaurant meal ($13) before

[31] I assume a constant walking speed of 3.5 miles per hour. Walking speed in Google Maps applications is about 3 miles per hour. Average reported walking speed in the NHTS is 4.4 mile per hour, and even faster for non leisure trips like walking to a restaurant, which appears implausibly fast. So I choose mid-range value of 3.5 miles per hour.

including transport costs. There is wide variation in the price index across areas. The index ranges from less than 6.5 in Manhattan and a few dense parts of San Francisco with faster car travel, to values around 10 in many of America's suburbs and small towns, and to values above 16 at the 99^{th} percentile of the index, in non-metropolitan areas with little gains from variety and hefty transport costs to reach even the nearest restaurant.

Shoup (2005) estimates that 99% of trips in the US end in free parking, but in high density downtown areas like Manhattan, accounting for parking fees would no doubt increase travel costs for car drivers.[32] Table 2, however, shows that in Manhattan even pedestrians face a low index of about 7.3, which is lower than the index for a car driver almost anywhere else in the US where parking is free.

An important result not apparent in Table 2 is that much of the variation in the index occurs within metropolitan areas. Over the entire sample of block groups, the price index for a car driver decreases by 38% from its 90^{th} to its 10^{th} percentile. Within the ten largest MSAs in the sample, the average decrease from the 90^{th} to the 10^{th} percentile of the index is 23%. This decrease is lowest in Miami at 14% and highest in New York, Houston and Atlanta at close to 30%. These large within-MSA variations in the index reflect the highly localized nature of the gains from restaurant density. Remote restaurants, which are expensive because of travel costs, have little impact on welfare. For instance, removing access to all restaurants lying between 30 and 45 minutes of travel reduces the price index on average only about 2%. This implies that individuals do not need perfect information on thousands of remote restaurants for these estimates to be valid.[33] The conclusion that the gains from restaurant density are localized may generalize to much of the consumption benefits of density, given relatively short trip times for most types of non-work trips in the NHTS.

[32]The time costs of cruising for parking and the walk between a parking spot and a restaurant is already included in trip time (if survey respondent filled their diary properly), and just translate into lower speed. Meters in lower Manhattan charge $3 per hour, and the average restaurant meal lasts 30 minutes, meaning that accounting for parking could increase the price index in Manhattan by as much as 1.50, probably less if some free parking is also available.

[33]I also estimate a version of the model in which restaurants farther away from an individual are known (i.e. part of her choice set) with a probability parameterized such that 100% of restaurants at 0 minute from home are known, and the probability of knowing restaurants farther away decreases with travel time. I find that individuals know about 69% of restaurants 45 minutes away, which barely affects the welfare estimates, but the results are not precise. I also estimate, by simulated maximum likelihood, a model in which the scale of the type I extreme value distribution of the error term decreases with distance, and obtain similar results.

Table 2: Percentiles of the restaurant price index

Percentile	Index by car	Index by foot	Example of location
Minimum	6.0	7.3	Manhattan
1^{st}	6.8	8.8	San Francisco
5^{th}	7.6	10.1	Downtown or near in most large cities.
10^{th}	7.9	10.7	Median location in Los Angeles County
25^{th}	8.5	11.7	Suburb/outskirt big central city, Downtown medium-sized city
50^{th}	9.3	13.4	Suburb
75^{th}	10.7	17.5	Remote suburb or small town
90^{th}	12.7	28.9	Country-side
95^{th}	14.0	38.7	Country-side
99^{th}	16.6	57.6	Country-side

Notes: The price index is computed using the estimate $\hat{\sigma} = 8.8$ from column (1) of Table 1. The percentiles are computed over all 51641 block groups in which there is at least one individual in the NHTS sample. The first row contains the lowest values in the sample.

A decline in the variety-adjusted restaurant price index translates into sizable welfare gains for an average household. For these welfare computations, ν is set to -1, consistent with a literature review by Okrent and Alston (2012) who find an average value of -1.02 for the price elasticity of demand for food away from home. Expenditure shares come from the Consumer Expenditure Survey (CEX) 2009, in which food away from home represents on average 5.3% of household expenditure, or $2619 out of average expenditures of $49,067. Using these numbers, and assuming that the price index for all other goods does not vary across areas, one can compute the aggregate relative price index in equation (6). In reality, the price index for all other goods *does* vary across areas, and in particular we expect higher house prices to cancel out the welfare gains from density. However, the goal of the present exercise is to compute willingness to pay for spatial variation in the availability of a consumption amenity holding everything else constant. I find that an average household's willingness to pay to enjoy a 20% decrease in the restaurant price index, which is equivalent to moving from a low to a high density part of a large MSA, is about $576 annually (as intuition suggests, $\$576 \approx 20\% * \$2619$, but see Appendix A for the details). The welfare estimates are not very sensitive to changing the price elasticity of demand for restaurants ν. Using a high elasticity of -2 instead of -1, the gains from a decrease in the price index are larger by about 7%.

Section D of the online appendix provides welfare estimates separately by income group, taking into account higher meal prices, higher value of time and faster travel speed for richer individuals. Richer household do enjoy considerably larger gains from restaurant density, but mostly because of higher expenditures on restaurants. Higher value of time and a slightly lower elasticity of substitution make small contributions towards increasing gains from density for high income individuals, but the relative prices computed from Table 2 are overall quite similar across income groups.[34]

It is interesting to compare these results with those of Handbury and Weinstein (2014), who estimate a variety-adjusted price index for tradable consumer goods (groceries with barcodes) in different MSAs. They find that residents of larger cities, controlling for store amenities, individual characteristics and differences in the number of varieties available, face a lower price index for groceries, a result entirely due to the availability of more varieties in larger cities. This price index drops by 5% from New York City, whose residents have access to 110,000 types of groceries, to Des Moines, the smallest city in their sample, whose residents have access to 24,000 grocery types. While these numbers are estimated for large areas and do not take transport costs into account, simple comparisons with my results for the restaurant industry suggest much larger spatial welfare differentials in the non-tradable service sector. Some residents of the New York or Los Angeles metropolitan areas have access to more than 20,000 restaurants within 45 minutes of car travel, versus only 800 in Des Moines, a city with faster travel speed. Moving from the densest part of New York City to the densest part of Des Moines leads to a 30% reduction in the price index (some of which is due to lower travel costs).

Future research may demonstrate that individuals derive similar benefits from the higher density of health providers, entertainment options and other services in the downtown cores of large metropolitan areas. In part, the dominance of non-tradables over tradables in explaining the consumption advantage of cities depends on the highly developed supply chains of the major consumer goods retailers. The low cost of moving goods enables the provision of

[34]Existing paper on how gains from variety vary by income group include Lee (2010), Li (2013) and Handbury (2012).

an impressive array of consumer goods to America's suburbs and smaller towns. Such feats of logistics are not easily replicated in the non-tradable service sector, which depends to a larger extent on the movement of people. Dense urban areas still have a unique advantage in reducing transport costs between individuals.

6.2 Where do welfare gains from density come from?

This section assesses the relative importance of the two sources of gains from density in the basic logit model: gains from variety and travel costs savings. For a given decrease in the index, a linear regression provides the share explained by travel time and fuel cost savings, with the remainder coming from gains from variety. I run regressions of restaurant trip time on 9 dummies $DummyR_k$ for the deciles of the variety-adjusted restaurant price index R_k, computed using the estimate of $\hat{\sigma}$ from column 1 in Table 1.[35] The omitted dummy is the first decile, so the regression provides the average increase in trip time within each upper decile of the index. The estimating equation is:

$$log(t_{nk}) = \alpha + \sum_{i=1}^{9} \gamma_d DummyR_{kd} + \beta_1 X_n + \beta_2 Z_n + \epsilon_{nk}. \qquad (8)$$

Each observation n is a trip and k indexes block group locations. The dependent variable t_{nk} is trip length in minutes for trip n in location k. Some specification contain a vector of individual characteristics X_n for the driver of trip n, such as age, income, speed and fuel costs, and a vector of trip characteristics Z_n, such as the number of individuals on the trip, and the time spent at destination.

The results are in Table 3. Row 1 shows that there is no significant differences in trip length between locations within the first and second deciles of the price index. The index, however, increases from 7.5 to 8.1. So for an individual in the second decile moving to the first decile, one can attribute 100% of the \$0.6 decrease in the index (the gains from density) to gains from variety and 0% to gains from shorter trips. Within the last decile, the index is equal to 14.5, so there is a \$7.0 difference in the index between the first and last deciles. Using the travel time difference on a one way trip of about 6.25 minutes from row 10 leads to a \$3.1 difference

[35] I include trips longer than 45 minutes in the sample, because in these regressions their inclusion affects the result, as very long trips are significantly more likely in low density areas with high values of the price index.

Table 3: Gains from shorter trip time

Travel time	(1)	(2)	(3)
Dummy 2^{nd} decile of price index	-0.23	-0.74	-0.90^{c}
	(0.56)	(0.52)	(0.49)
Dummy 3^{rd} decile of price index	0.64^{a}	0.37	0.12
	(0.52)	(0.52)	(0.49)
Dummy 4^{th} decile of price index	1.93^{a}	1.41^{b}	1.04^{b}
	(0.55)	(0.57)	(0.52)
Dummy 5^{th} decile of price index	1.43^{a}	1.01^{c}	0.49
	(0.52)	(0.54)	(0.51)
Dummy 6^{th} decile of price index	2.93^{a}	2.70^{a}	2.05^{a}
	(0.54)	(0.56)	(0.52)
Dummy 7^{th} decile of price index	2.12^{a}	2.10^{a}	1.80^{a}
	(0.53)	(0.55)	(0.51)
Dummy 8^{th} decile of price index	3.33^{a}	3.44^{a}	2.70^{a}
	(0.55)	(0.57)	(0.54)
Dummy 9^{th} decile of price index	4.78^{a}	5.18^{a}	4.36^{a}
	(0.61)	(0.64)	(0.61)
Dummy 10^{th} decile of price index	6.52^{a}	6.65^{a}	5.60^{a}
	(0.88)	(0.93)	(0.88)
Controls			
Individual characteristics		X	X
Trip characteristics			X
Observations	7510	6896	6896
R^2	0.03	0.05	0.14

Notes: OLS regressions in all columns. Robust standard errors, clustered at the county level, in parentheses. a, b, c: significant at 1%, 5%, 10%. The dependent variables is trip time in minutes. The excluded price index dummy is that for the 1^{st} decile of the index. The sets of individual and trip characteristics are the same as in Table 5.

in travel costs between the first and last deciles.[36] So one can attribute about 3.1/7 = 44% of the gains from density to shorter trips. Repeating the same exercise for the remaining deciles leads to shares of travel costs savings in the gains from density that are lower than 44%.

It is instructive to consider additional, non-structural, evidence on the importance of gains from variety in denser areas. The number of restaurants passed by a traveler on her way to her

[36]Time saving on a round trip is $6.25 * 2 = 12.5$ minutes, valued at $(12.5/60) * 12 = 2.5$ dollars. Fuel costs for a 12.5 minute trip, at average speed, fuel efficiency, and gas prices is about $0.6, which leads to total travel costs savings of $2.5 + 0.6 = 3.1$ dollars.

final destination is arguably a measure of whether an individual chooses to visit a 'preferred' destination. The median number of restaurants passed is 14 within the first decile of global density, and it rises steadily up to 89 in the last, denser decile. These numbers strongly suggest that travelers in dense areas often visit destinations closer to their ideal.

These results imply that the main effect of policies promoting denser developments is to allow individuals to visit places that they prefer. That being said, denser areas also generate gains from shorter trips, especially relative to very low density areas in which even the closest restaurant is far from home.

7. Robustness: specification tests, extensions and sensitivity analysis

This section first uses regression analysis to test model specification and to investigate the possibility that individuals sort by density levels according to unobservable characteristics.[37] The section then covers various extensions of the model addressing potential misspecification issues raised in the reduced-form analysis. These extensions allow for the sorting of restaurants and individuals across areas. The section concludes with a sensitivity analysis of welfare estimates to changes in parameter values and estimation sample.

7.1 Reduced-form analysis

The reduced-form analysis requires measures of restaurant density. The following four measures capture the key features of the spatial distribution of restaurants uncovered in section 4:

1. *Travel time to the closest restaurant*
2. *Local restaurant density* passed the closest restaurant, in restaurants per minute, equal to travel time to the 20^{th} closest restaurant minus travel time to the closest restaurant, divided by 19.

[37] Regressions on the determinant of trip time are interesting in their own rights. For instance, the relationship between travel and the built environment is crucial when evaluating urban development schemes designed to reduce vehicle travel. The online appendix presents complementary results on the determinants of the probability of making a restaurant trip.

3. *Global restaurant density* for an area wide enough to encompass most trips, but not so large as to be irrelevant to a traveler, equal to the number of restaurants available within 45 minutes of travel, divided by 45.

4. *Skewness*, which captures whether most of the restaurant mass is distributed close to or far from an individual, equal to the density of restaurants from 22.5 to 45 minutes of travel over the density of restaurants from 0 to 22.5 minutes of travel.

7.1.1 Testing the model: regressions on measures of restaurant density

A key prediction of a travel demand model with gains from variety is that increasing restaurant density has little effect on trip time, because density makes it cheaper to substitute between restaurants and to visit a location that one prefers. The first step in testing this prediction is to state it precisely by finding the exact impact that measures of restaurant density would have on trip time if the logit model were true. This requires creating a dependent variable equal to *predicted* average trip time for each traveler in the sample, which can then be used in regressions on measures of restaurant density.[38] I then run the same regressions, but using *actual* trip time as a dependent variable. If regressions on actual and predicted trip times generate similar coefficients, then the model accurately predicts the actual impact of restaurant density on trip time.

Regressions on predicted trip time The model predicts the probability of traveling to any given restaurant from each location, given T_k, F_k and $\hat{\sigma}$. Using the predicted probability of a trip of each length in an area k, I compute $\bar{t}_{nk}$, the model's prediction of expected trip time for each trip n in the sample. The estimating equation for an OLS regressions using $\bar{t}_{nk}$ as a dependent variable is:

$$log(\bar{t}_{nk}) = \alpha + \beta_1 density_k + \epsilon_{kn}, \tag{9}$$

[38]Note that if the distribution of restaurant was always uniform, the predicted impact of an increase in density on trip time would be 0 because of the IIA, and this step would not be necessary.

Table 4: The determinants of trip times, predictions from the logit model

	(1)	(2)	(3)	(4)
log Predicted average trip time ($\bar{t}$)				
log Global density	0.089^{a}		0.138^{a}	0.210^{a}
	(0.004)		(0.004)	(0.004)
log Skewness		0.062^{a}	-0.025^{a}	-0.089^{a}
		(0.005)	(0.004)	(0.004)
log Time to closest rest.			0.518^{a}	0.588^{a}
			(0.009)	(0.008)
log Local density				-0.210^{a}
				(0.006)
Observations	7407	7405	7405	7405
R^2	0.09	0.05	0.59	0.73

Notes: OLS regressions with a constant in all columns. Robust standard errors, clustered at the county level, in parentheses. a, b, c: significant at 1%, 5%, 10%.

where $density_k$ represents characteristics of the restaurant distribution in area k (travel time to closest restaurant, local density, global density, and skewness). The sample of restaurant trips is that used to estimate the model.

Regression on actual trip time The estimating equation for regression on actual trip time is:

$$log(t_{nk}) = \alpha + \beta_1 density_k + \beta_4 X_n + \beta_5 Z_n + \epsilon_{nk}. \tag{10}$$

The independent variables are as in equation (9), except that some specifications include a vector of individual characteristics X_n and of trip characteristics Z_n.

Table 4 reports the regression results using predicted trip time and Table 5 reports the regression results using actual trip time. It is important to emphasize that regression results in Table 4 capture general properties of the logit model and do not depend on using fitted parameter values. All coefficients in both tables are elasticities. The four measures of restaurant density are correlated with one another, so the coefficient on each variable is sensitive to the inclusion of the others. Comparison of results in Table 5 with the predictions in Table 4 demonstrate the logit model's remarkable ability to match key features of the travel data.

Table 5: The determinants of trip time

log Trip time to restaurant	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log Global density	-0.017^b		0.002	0.037^a	0.033^a	0.036^a	0.017
	(0.007)		(0.008)	(0.009)	(0.009)	(0.009)	(0.023)
log Skewness		0.036^a	0.009	-0.012^b	-0.009	-0.007	0.009
		(0.006)	(0.007)	(0.007)	(0.008)	(0.007)	(0.012)
log Time to closest rest.			0.232^a	0.271^a	0.252^a	0.231^a	0.231^a
			(0.018)	(0.018)	(0.018)	(0.017)	(0.024)
log Local density				-0.111^a	-0.112^a	-0.098^a	-0.123^a
				(0.013)	(0.014)	(0.013)	(0.020)
Controls							
Individual characteristics					X	X	X
Trip characteristics						X	X
MSA fixed-effects							X
Observations	7407	7405	7405	7398	6791	6712	5543
R^2	0.001	0.005	0.035	0.043	0.070	0.168	0.173

Notes: OLS regressions with a constant in all columns. Robust standard errors, clustered at the county level (except in column 9), in parentheses. a, b, c: significant at 1%, 5%, 10%. Dependent variable is log trip time to restaurant in all columns. Individual characteristics include 17 dummies for household income, 4 dummies for education, household size, 6 dummies for age, a dummy for gender, a dummy if black, a dummy for worker's status, the speed of a one mile trip (which depends on individual characteristics and census tract), and gasoline costs per mile at medium speed (which depends on vehicle type and gas prices). Trip characteristics include 5 dummies for each peak hour (7-8am, 8-9am, 15-16pm, 16-17pm, 17-18pm), a dummy for trips on week-end, the number of children on the trip, the number of adults on the trip, the number of non-household members on the trip, and the log time spent at destination.

Columns 1–4 of Table 5 present regression results with only measures of restaurant density as controls and correspond exactly to the four columns of Table 4.[39]

As predicted, the elasticity of trip length with respect to travel time to the closest restaurant is large and positive in all specifications. The elasticity of trip time with respect to skewness is positive and significant, as predicted, when it enters alone in column 2, so that individuals indeed take shorter trips if the mass of restaurants within 45 minutes is disproportionately

[39]The low R^2 of the regressions in Table 5 is expected, and consistent with the inherent randomness in discrete-choice decision making. The R^2s in Table 4 are higher because the dependent variable in these regressions is average predicted trip time. In this case, the R^2 reflects the ability of measures of restaurant density to capture the features of the restaurant distribution that determine average predicted trip time.

located close to home. Local density has the predicted negative effect on trip time in all specifications, so travelers with a high density of restaurants close to home (passed the closest restaurant) make shorter trips. Clearly then, the decision of how far to travel strongly depends on the spatial distribution of restaurants, in ways that can be predicted. Columns 5, 6 and 7 add controls for individual and trip characteristics and an MSA fixed-effect, which barely affect the coefficients on measures of restaurant density.

The key difference between regressions on predicted logit travel time and regressions on actual travel time is the coefficient on global density. This coefficient is close to zero in each regression on actual trip time, meaning that the number of restaurants available within 45 minutes of travel has little impact on trip time. That increasing global density fails to reduce trip time in the data corroborates the intuition behind the model, that substituting among travel destinations is cheap in dense areas, so individuals often gain from density by visiting preferred locations. However, this zero effect does not match the model's prediction of a significant positive effect, a prediction due to the larger share of the restaurant mass located far from home in dense areas.

Despite this discrepancy, the very small (actually *positive*) effect of density on travel time in the data is an important finding, because it suggests that additional restaurants in dense areas are not superfluous. This is contrary to the results for the retail sector in Handbury and Weinstein (2014), who find that additional varieties in larger cities account for a relatively low share of expenditures and are presumably low quality. This result likely reflect the ability of markets in non-tradables - the focus of this paper - to respond to local tastes, which is an assumption in the nested-logit model of Section 7.2.

To summarize, the logit model matches the first-order features of the data, but there is a discrepancy between the actual and predicted effect of the number of restaurants within 45 minutes of travel (global density) on trip time, which could mean that some assumptions underlying the logit model are too strong. I offer three explanations. First, the IIA may not hold, and remote restaurants may be close substitutes for options available closer from home, so the mass of restaurants far from home in dense areas exert less attraction on a traveler. Extensions of the model in subsection 7.2 relax the IIA property of the logit model. Second, measurement error biases OLS estimates towards zero. Third, omitted variables can bias the coefficient on global density. An instrumental variable strategy alleviates both measurement error and omitted variable biases.

7.1.2 IV estimation

If individuals sort into areas based on γ or σ, then OLS coefficients are biased because of a correlation between the error term in equation (10) and measures of restaurant density. For instance, the model predicts that individuals with high value of travel time make shorter trips. Therefore, sorting of high γ individuals into dense areas could explain why the model - in which there is no sorting - overestimates trip length in areas with high global density. If this is the case, the IV coefficient on global density will be more positive than its OLS counterpart, and closer to the model's prediction. The reverse happens if individuals with marginal preferences or pronounced taste for variety sort into dense areas; with sorting on σ the coefficient on global density should become more negative if instrumented.

An instrument z_k for global density in location k must satisfy two criteria. First, it must be relevant, i.e. correlated with global density conditional on other controls: $corr(global\_density_k, z_k|controls) \neq 0$. Second, the instrument must be exogenous, i.e. uncorrelated with the error term: $corr(\epsilon_{nk}, z_k|controls) = 0$. The instrument for global density is growth in population density from 2000 to 2007 in the county in which an individual lives. This IV strategy depends crucially on the ability to select a sample of individuals - old, married, homeowners - who are very unlikely to move out of county in any given year.

The county population data come from the Census in 2000 and from the 2005-2009 population averages from the American Community Survey in 2007. Population density is population count over area. The growth in population density from 2000 to 2007 is the ratio of the log density in 2007 to that in 2000.

While counties vary in size, they are the census geographic units that most closely match an area accessible through 45 minutes of travel.[40] Current county population density is a strong

[40]The median county in my sample has a radius of about 38 miles, while 45 minutes of driving usually covers about 25-30 miles.

predictor of restaurant global density. More important, growth in county population density in the 2000s explains variations in the level of restaurant global density in 2011, especially if one controls for initial county population density in 2000.[41] So the instrument is relevant.

If individuals sort into densely populated areas based on unobserved characteristics that affect trip time, then the instrument fails the exogeneity condition. Using growth to instrument a level is an important step towards satisfying the exogeneity condition. One can also control for the initial level of population density in 2000, and people probably seldom choose to reside in an area based on an accurate prediction of its density growth prospect a few years hence. Therefore, the main threat to the exogeneity condition comes from individuals who moved between 2000 and 2007 into areas whose population densities were high because of recent growth. In this case, there is sorting on the instrument. This is a particular concern because 15.4% of Americans surveyed by the 2009 ACS had changed residence over the previous year, according to Ihrke, Faber, and Koerber (2011). To remedy this, the identification strategy relies on creating a sample of individuals with a low probability of moving out of county in any given year. The moving rate of individuals aged 45 and older is about 7%, with only a 3% chance each year of moving out of county. Homeowners have a 6.7% moving rate, almost five times smaller than that of renters. Married individuals also have a lower than average moving rate at 9.9%. Keeping in mind that older individuals are also more likely to be married and to own a home, suppose that 2.5% of married homeowner 55 years and older randomly move out of county every year.[42] In this case, more than 80% of these older, married, home-owning travelers in the 2008-2009 NHTS lived in the same county in 2000. The IV regressions are therefore informative, but one should treat the results with caution.

Table 6 contains the two-stage least squares estimation results. The estimates in columns 1–4 are for the full sample, and those in columns 5–8 are for the sample of individuals with a low probability of moving. In each column, the elasticity of trip time with respect to global density is positive and significantly larger than any of the OLS elasticities. This result is consistent with

[41] Without a control for initial population density, the instrument is marginally weak (columns 1 and 5 of Table 6).

[42] I keep individuals 55 years and older instead of 45 years and older because a 45-year-old in 2008 was 37 in 2000. I observe both age and home ownership status in the NHTS and I select individuals living in households with two or more members to proxy for marital status.

Table 6: The determinants of trip time, with instrument for global density

Trip time to restaurant	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8))
log Global density	0.085	0.078^{c}	0.118^{b}	0.099^{b}	0.180^{b}	0.161^{b}	0.212^{a}	0.169^{b}
	(0.054)	(0.047)	(0.050)	(0.049)	(0.077)	(0.065)	(0.070)	(0.082)
log Time to closest rest.			0.249^{a}	0.262^{a}			0.340^{a}	0.262^{a}
			(0.022)	(0.024)			(0.034)	(0.036)
log Skewness			-0.050^{a}	-0.032			-0.075^{a}	-0.055^{b}
			(0.018)	(0.02)			(0.023)	(0.025)
log Local density			-0.124^{a}	-0.163^{a}			-0.188^{a}	-0.147^{a}
			(0.019)	(0.023)			(0.033)	(0.033)
Controls								
log County pop. density in '00		X	X	X		X	X	X
Individual characteristics				X				X
Trip characteristics				X				X
Instrument								
Δ log County pop. density '00-07	X	X	X	X	X	X	X	X
Samples								
Full sample	X	X	X	X				
Low probability of moving					X	X	X	X
Observations	7390	7390	6704	6587	3528	3528	3182	3126
First-stage stat.	14	31	30	18	11	27	28	17

Notes: Two-stage least squares regressions with a constant in all columns. Robust standard errors, clustered at the county level in parentheses. *a*, *b*, *c*: significant at 1%, 5%, 10%. Dependent variable is log trip time to restaurant in all columns. The sets of individual and trip characteristics are the same as in Table 5. The sample with a low probability of moving consists of all homeowners 55 years and older living in an household with at least 2 members. The first-stage F statistics are cluster-robust.

the sorting of individuals with high value of travel time, who are predicted to make shorter trips, into dense areas. The elasticities range from 0.07-0.12 in columns 1–4 and are twice as large in columns 5–8, suggesting that sample selection is important for identification (sample selection does not matter nearly as much in the OLS). For this sample of individuals with a low probability of moving, one cannot reject the hypothesis that the effect of global density on trip time is the same as that predicted by the model. The regression with all measures of density, in column 7, generates results remarkably similar to those obtained from predicted average trip time data in column 5 of table 4. The IV strategy probably mitigates the impact of measurement error, as it moves all coefficients on measures of restaurant density away from 0 and towards the model's prediction.[43]

7.2 *Extensions of the logit model*

This section presents four extensions of the logit model of travel demand. The first extension allows for the sorting of individuals into denser areas by value of travel time, in line with the IV regression results. The second lets meal prices vary with travel time from home, to investigate a potential source of bias in my estimates. The last two extensions relax the IIA property of the logit model and allow for the diversity of restaurants to vary across areas.

7.2.1 *Sorting by value of time*

IV regressions indicate that individuals who choose to live in high restaurant density areas make shorter trips, and the model suggests that sorting by value of travel time can explain this result. In this extension of the basic logit model, an individual's value of travel time γ is a function of global density in location k. The parameter σ is estimated jointly with a new parameter β capturing the strength of the relationship between γ and density. The estimation results are in Table 1 and the details of this model are in Section F of the online appendix. The elasticity of substitution $\hat{\sigma} = 8.4$ is slightly lower than in the model without sorting, which implies marginally higher gains from density. Most important, the model with sorting predicts the OLS regression results of a near zero effect of global density on trip time. Recall that the model without sorting predicts the IV regression results of a positive effect of global density on trip time.

7.2.2 *Variation in meal prices*

Data from Yelp.com provides a way to evaluate the estimates' sensitivity to price variation across areas. A particular concern is that higher density implies higher restaurant prices or better quality. Yelp data is available only for 23% of restaurants, all in the 20 largest MSAs in the sample. The small positive correlation between average meal price and restaurant

[43] The variables for local density and travel time to the closest restaurant are also endogenous, but the instrument (even if defined at the census tract instead of at the county-level) is much weaker for these variables, and these IV regressions are sensitive to the set of controls and often lead to unreasonable values.

density within 45 minutes of travel is too weak to significantly impact welfare estimates. Price differences across MSAs are also too small to affect the welfare results. Average quality ratings have almost no correlation with density levels, and display little geographic variation.[44] One should interpret these results with caution, because the Yelp price data is coarse and available only for a selected sample of restaurants, and Yelp ratings often originate from local residents and are not necessarily comparable across areas. So while restaurants are one of the best example of horizontal differentiation, future datasets from constantly evolving online applications will hopefully help illuminate the importance of vertical differentiation.

An alternative way of assessing the importance of price variation across density levels is to focus on a standardized restaurant item like McDonald's Big Mac. The Economist's Big Mac index is already a popular way of assessing price differences across countries. Landry (2013) collected data on Big Mac prices within New York City, and identified sizable spatial variation in prices. Perhaps surprisingly, the average price in locations within 0 to 4 miles from Manhattan's Penn Station is $3.95, and this average price actually increases to $4.02 in locations farther from the high density core of New York City (4 to 17 miles from Penn Station). So while it is suggestive that New York City serves some of the most expensive Big Macs in the U.S., these numbers are inconsistent with a significant drop in prices as density declines within a city, and do not undermine the validity of the paper's key finding of a large drop in the restaurant price index as one travels to the high density center of a city.

Assuming a constant meal price can also bias welfare estimates if the characteristics of restaurants close to home differ systematically from those of restaurants far from home. For instance, a majority of travelers live in suburbs, relatively far from downtown restaurants which tend to be slightly more expensive and upscale and to feature rarer restaurant types (e.g. French). To remedy this, I use data from Yelp to compute average characteristics of restaurants that vary with travel time from home. Again, restaurants' characteristics in general and quality ratings in particular are surprisingly constant across areas and travel time, although restaurants far from home are on average pricier, have more reviews, a more

[44] Berry and Waldfogel (2010) also do not find evidence that average restaurant quality increases with market size.

upscale ambience and attire, are more likely to require a reservation and less likely to have easy parking. The average price of a restaurant within 0–5 minutes of travel from home is 7.5% lower than that for restaurants 40–45 minutes away. So I re-estimate the logit model, but with meal price varying in each time bin. I normalize the meal price of restaurants between 20–25 minutes from home at exactly 13 to be consistent with other estimations. I find $\hat{\sigma}$ = 8.4 (column 4 of table 1). A model in which only the meal price varies with trip time provides a lower bound for σ, because restaurants farther from home are not just more expensive; they are also more upscale. This elasticity of substitution is slightly lower than that from the model with constant meal prices, and the welfare gains from density are correspondingly slightly larger.

7.2.3 Redundant chain restaurants

Restaurants within a given chain are never exactly similar, but clearly two McDonald's are highly substitutable with one another, and a model in which restaurants in the same chain are perfectly substitutable may be a better representation of reality. This is perhaps the simplest way to relax the logit assumption that all restaurants be equally substitutable (IIA property), and to introduce restaurant diversity into the model. Intuitively, areas consisting mostly of repeated chain restaurants have low diversity.

Because travel is costly, a restaurant that is perfectly substitutable with another restaurant closer from home is never visited, and all repeat chain restaurants are removed from each traveler's choice set.[45] Estimation is then exactly as in the logit model, with the estimator given by equation (7). I find $\hat{\sigma} = 8.4$ (column 5 of table 1). This extension generates predictions on the effect of global density on trip time that are only marginally closer to the data. The gains from density are slightly larger in the model with substitutable chains due to a lower σ than in the basic model.

[45]To estimate this model, I code the 50 largest restaurant chains in my data, which represent 23% of all restaurants in the sample, and are likely to occur more than once within 45 minutes of travel. Note that repeat chain restaurants account for a smaller proportion of restaurants in denser areas, contrary to an intuition that would be correct if restaurants were randomly distributed.

7.2.4 *Nested-logit model*

In a nested-logit model, individuals first choose a category of restaurants (e.g. pizza, Chinese, burger or vegan) and then decide which restaurant to visit within that category. The IIA property of the logit model does not hold, because restaurants within the same category are more substitutable.

There are 85 categories of restaurants, indexed by c, and representing different types of cuisine.[46] I first assume that taste for categories is constant across categories and locations, and then I relax this assumption. As before, each restaurant receives a type I extreme value idiosyncratic shock ϵ_{kci}, but now each restaurant also receives a category-specific type I extreme value idiosyncratic shock ς_{kc}. The utility from choosing restaurant i from category c in location k is:

$$u_{kci} = (1-\sigma)ln(p_{kci}) + \epsilon_{kci} + \frac{1}{\mu - 1}\varsigma_{kc}.$$

The full derivation of the probability $prob(t_{kci}|\sigma, \mu, T_k, F_k)$ of traveling to each restaurant is in section F of the online appendix. The advantage of this utility specification is that μ has an interpretation as an elasticity of substitution across categories, and the resulting choice probabilities are exactly as in a nested-CES model, as in Sheu (2014).

Let n index each trip t_{nk} in the sample. To estimate the model without data on the category of restaurant visited on each trip, define $R_{nk}(t_{nk})$ as a set of restaurants at travel time 'close' to actual trip time t_{nk} in the choice set T_k. With a slight abuse of notation, let i index all restaurants in R_{nk}, so the log-likelihood function becomes:

$$\ell(\sigma,\mu,T_N,\mathbb{T}_K,\mathbb{F}_K) = \sum_{n=1}^{N} log\left(\sum_{i\in R_{nk}(t_{nk})} prob(t_{kci}|\sigma,\mu,T_k,F_k)\right),$$

and the maximum likelihood estimator is:

$$(\hat{\sigma},\hat{\mu}) = \underset{\sigma,\mu}{\text{argmax}}\ \ell(\sigma,\mu,T_N,\mathbb{T}_K,\mathbb{F}_K). \tag{11}$$

[46] The categories, and their percentage share, are listed in Section F.4 of the online appendix. The category is 'undefined' for 17% of restaurants, usually smaller independent places serving standard fares. The next largest categories are Pizza (9.3%), Mexican (9.3%), American (9.1%), Burger (7.5%) and Chinese (6.3%). There is no category for casual dining 'family' restaurants, and such establishments are generally included in the 'Undefined' and 'American' category.

Defining R_{nk} as the set of all restaurants within 5 minutes of actual trip time t_{nk} delivers estimates of $\hat{\sigma} = 8.4$ and $\hat{\mu} = 9.9$, with μ imprecisely estimated. Given that $\sigma = \mu$ corresponds to the logit model, this result may suggest that the nests for types of cuisine are unnecessary.

These estimates, however, are problematic because they assume constant tastes for categories, so that pizza and vegan restaurants are equally desirable. This assumption overstates the attraction of small and arbitrary categories. Moreover, the restaurant cuisines available in a particular area probably reflect the tastes of individuals who live there, as shown in Waldfogel (2008). That is, individuals may live on average closer to their preferred restaurant type, and one should not infer a low preference for variety from these short trips. To address this joint sorting of individuals and restaurants, I add a location-specific distribution of tastes for restaurant categories to the model, with a parameter b_{kc} capturing the taste for category c in location k.[47] The utility function becomes:

$$u_{kci} = \frac{1}{\sigma - 1} ln(b_{kc}) - (\sigma - 1) ln(p_{kci}) + \epsilon_{kci} + \frac{1}{\mu - 1} \varsigma_{kc}.$$

Section F of the online appendix shows how introducing restaurant supply in the model allows the derivation of taste parameters b_{kc} from observed restaurant density in each category.[48] Estimating the model with location specific tastes for restaurant categories, delivers estimates of $\hat{\sigma}$ = 9.2 and $\hat{\mu}$ = 3.6, with $\hat{\mu}$ having a large standard error of 0.25 (column 7 of Table 1). That σ is larger than μ suggests that travelers care more about restaurant cuisine than about the particular restaurant serving that cuisine. The nested-logit model predicts trip length in areas with high global density better than the logit model (30% closer to the data). Long trips in dense areas become unnecessary, because some of the thousands of restaurants far away from home belong to categories available closer to home.

[47] If, similar to Handbury and Weinstein (2014), I assumed instead that tastes were constant across the United States, then percentile differences in the index across and within cities would stay relatively similar, but, for instance, some areas in Texas with a vast majority of Mexican restaurants would wrongly receive a high price index from a model that does not let Texans have a special taste for Mexican food. Schiff (2015) shows that even if preferences are identical everywhere, densely populated areas in a free-entry model feature more categories of restaurants, because they contain enough people with marginal tastes to make restaurants in the least popular categories profitable. This argument is intuitive, but it alone cannot account for the wide range of restaurant diversity that I measure in areas at the same density level. For instance, some areas in Texas contain a large share of Mexican restaurants, which likely reflects local tastes for this type of cuisine.

[48] Note that I obtain analytical results from a continuous version of the model with uniform density.

Assuming that individuals always move to areas with exactly the same share of each cuisine as that in their original location, the 90^{th} to 10^{th} percentile differential in the restaurant price index is about 42%, or four percentage point higher than that computed from the logit model. Hence, accounting for restaurant diversity and local tastes increases the gains from density.

7.3 Sensitivity analysis

Section C of the online appendix provides a sensitivity analysis. The magnitude of the welfare estimates are robust to variation in σ well within the range suggested by the model's various specifications. The welfare estimates depend heavily on the estimated parameter σ, and are much less sensitive to variation in the parameter γ taken from the literature. Estimates of σ are robust to various sample definitions, such as keeping trips that do not start from home.

8. Conclusion

This paper shows how to estimate the consumption value of density by combining travel data with microgeographic data on local businesses. Individuals' substitution patterns among travel destinations reveal gains from urban density that are large but localized. These gains originate in part from shorter trip times, but mostly arise because increased choice in denser areas allows individuals to visit destinations that they prefer. This result explains why empirical studies fail to uncover large reductions in travel as density increases, and shows that popular policies designed to reduce vehicle travel will instead have larger impacts on increasing gains from variety. The consumption benefits of density in the restaurant industry demonstrate that cities, and downtown cores in particular, enjoy a large advantage in non-tradable service provision.

Finally, this research helps move the focus of transportation research in economics from travel speed and congestion to the broader concept of accessibility. The relatively low median value of the index for car travelers supports the argument in Glaeser and Kahn (2004) that the suburban lifestyle shared by a majority of Americans offers good accessibility through fast car travel. However, the lowest price index, or equivalently the best accessibility, belongs to areas with the *slowest* car travel. Raising the density of destinations, of population and of the street network reduces travel speed, but not enough to annihilate the benefits from greater access to destinations. Moreover, driving loses its attractiveness in very high density areas, due to low car travel speed bringing values of the car and walk price index closer together. This explains why a sizable majority of Manhattanites walk to restaurants. This suggests that raising density and promoting "walkability" can indeed reduce vehicle use, as argued by New Urbanism proponents. This only happens, however, at very high levels of density that are rarely seen in the modern American landscape.

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Appendix A. Derivation of aggregate relative price index

The linear utility specification of a nested-logit model with one nest for restaurants and one nest for all other goods is similar to that in the nested-logit model of Section 7.2. An individual first solves the maximization problem within the restaurant nest (exactly as in Section 3) and within the nest for all other goods. Then she solves the aggregate utility maximization problem by choosing expenditure shares on restaurants and on all other goods. Denote the elasticity of substitution between restaurants and all other goods by ν. It is easy to show that ν is exactly equivalent to (the negative of) a price elasticity of demand for restaurants, for which estimates exist. For instance the elasticity suggested by Okrent and Alston (2012) corresponds to the limiting case $\nu = 1$.[49] The aggregate relative price index between area k and k' is:

$$P_{k,k'} = \frac{(R_{k'}^{1-\nu} + G_{k'}^{1-\nu})^{1/(1-\nu)}}{(R_{k}^{1-\nu} + G_{k}^{1-\nu})^{1/(1-\nu)}}, \tag{A1}$$

where R_k is the price index for restaurants (from equation 5) and G_k is the price index for all other goods. As shown in Sato (1976) and Vartia (1976), one can express the relative price index above in terms of expenditure shares. For instance, if $s_{Rk'}$ is the expenditure share on restaurants in area k', then:

$$P_{k,k'} = \left(\frac{G_{k'}}{G_k}\right)^{w_{Gk'}} \left(\frac{R_{k'}}{R_k}\right)^{w_{Rk'}},$$

where:

$$w_{Rk'} = \frac{(s_{Rk'} - s_{Rk})/(ln(s_{Rk'}) - ln(s_{Rk}))}{(s_{Rk'} - s_{Rk})/(ln(s_{Rk'}) - ln(s_{Rk})) + (s_{Gk'} - s_{Gk})/(ln(s_{Gk'}) - ln(s_{Gk}))}.$$

I assume that the price index for all other goods is constant across areas, so that $G_k = G_{k'}$. At $\nu = 1$ the expenditure share on restaurants is constant, so that $s_{Rk} = s_{Rk'}$ for any areas k and k'. If $s_{Rk'}$ is arbitrarily close to s_{Rk}, then we can find $w_{Rk'}$ as: $\lim\limits_{s_{Rk} \to s_{Rk'}} w_{Rk'} = s_{Rk'}$.

[49] It is standard to assume that $\nu > 1$, but the welfare estimates are not sensitive to using, say $\nu = 1.02$ - exactly as in Okrent and Alston (2012) - instead of $\nu = 1$.

With data on expenditure shares, it is now possible to compute the aggregate relative price index and to measure the average household's willingness to pay to enjoy a 20% decrease in the restaurant price index. The 2009 CEX suggests that food away from home accounts for 5.3%, of total expenditures, so that $s_{Rk'}$ = 0.053. The aggregate relative price index becomes $P_{k,k'} = \left(\frac{G_{k'}}{G_k}\right)^{w_{Gk'}} \left(\frac{R_{k'}}{R_k}\right)^{w_{Rk'}} = (1) \left(\frac{R_{k'}}{R_k}\right)^{s_{Rk'}} = 0.8^{0.053}$ = 0.98824. The average total household expenditures in the CEX 2009 is about $49,067, so the average household's willingness to pay for a 20% decrease in the restaurant price index is $49{,}067(1 - 0.98824)$, which equals $576.[50]

Appendix B. Data

A. Travel speed

Estimates of car travel speed for a trip of a given distance in a given location come from regressions of log of trip speed on the log of trip distance for the entire NHTS sample of car trips, with a fixed effect at the census tract level to capture speed variation across areas. Measuring speed as a function of trip distance allows longer trips to be faster, because they are taken mostly on faster roads like highways.[51] Let n index each trip and its driver, and k index the census tract in which an individual lives. Let $speed_{nk}$ and $distance_{nk}$ denote the speed and distance of trip n in census tract k. The estimating equation is:

$$ln(speed_{nk}) = \alpha + \beta_1 ln(distance_{nk}) + \beta_2 X_n + \theta_k + \epsilon_{nk}, \quad \text{(B1)}$$

where X_n is a vector of individual characteristics in some specifications. Longer trips are on average faster, with an elasticity of 0.42, precisely estimated. Richer, younger and more educated individuals drive faster.

[50] To compute welfare gains when the elasticity of demand is higher, say at $\nu = 2$, note that $\frac{s_{Rk}}{s_{Rk'}} = \frac{R_k}{R_{k'}}^{1-\nu} P_{k,k'} \approx \frac{R_k}{R_{k'}}^{1-\nu}$. For a household with average expenditures, a 20% decrease in the restaurant price index increases the expenditure share on restaurants from $s_{Rk} = 0.053$ to $s_{Rk'} = 0.06625$ and generates welfare gains valued at $617, a 7% increase relative to the case with $\nu = 1$.

[51] See Couture, Duranton, and Turner (2016) for additional details on these regressions.

B. *Fuel cost*

The NHTS contains data on daily gasoline prices in five broad regions and vehicle types in four categories (car, van, SUV, pickup truck and other trucks). To each type of vehicle, I assign the fuel efficiency of the best selling vehicle of this type in 2000.[52] For instance, the best selling pickup in 2000 was the F-150. The other best selling vehicles in each category are the Toyota Camry (car), Ford Explorer (SUV) and Dodge Caravan (van). The relationship between fuel consumption and trip distance is nonlinear, because vehicles are less efficient at very low or very high speeds. Based on West, McGill, and Sluder (1999)'s numbers, I assume that each vehicle reaches maximum fuel economy at speeds between 25 and 60 miles per hour, and consumes 20% more at speeds exceeding 60 mph or below 25 mph. Maximum fuel economy is the value reported for 'highway' consumption by the Department of Energy, which is 19 miles per gallon (mpg) for the Ford F-150, 28 mpg for the Toyota Camry, 19 mpg for the Ford Explorer and 24 mpg for the Dodge Caravan.[53] Speed at any point on a trip come from fitted values from equation (B1), which provides average speed as a function of distance. As an example, if an individual takes a 10 miles trip in a pickup, and reaches 25 mph after 5 miles but never reaches a speed beyond 60 mph, then his total fuel consumption in gallons is: $5\text{ miles}/(19 * (1 - 0.2)\text{ mpg}) + 5\text{ miles}/19\text{ mpg}$. Fuel cost for a trip is then the product of total fuel consumption and fuel price.

[52] 2009 models are not representative of the actual stock of vehicles on the road in 2009, which is on average 10 years old. The data on the best selling vehicles of 2000 is from Edmunds.com, an online source of information on the American vehicle market. Available online at `http://www.edmunds.com/car-reviews/top-10/top-10-best-selling-vehicles-in-2000.html`, retrieved 10 September 2013.

[53] The data is available online. For instance information on the F-150 is at `http://www.fueleconomy.gov/feg/bymodel/2000_Ford_F150_Pickup.shtml`, retrieved 10 September 2013.