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Income Inequality and Product Variety: Empirical Evidence

Dieter Pennerstorfer* Nora Schindler† Christoph Weiss† Biliana Yontcheva‡

October 2020

Abstract

This article investigates the relationship between income inequality and firms' locations and product choices. Using detailed information on income at a regionally disaggregated level and individual data on Austrian restaurants, we demonstrate that firm conduct crucially depends on the distribution (in addition to the level) of income. Local markets with higher income inequality are characterized by a larger number of firms, offering a broader range of products and product variants that are on average less common. These findings indicate that local demand is substantially influenced by the heterogeneity in consumers' income endowments, resulting in large differences in product variety.

Keywords: income inequality, product variety, product differentiation, firm conduct, restaurants

JEL Codes: L22, D31, R12, L83

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1 Introduction

Many Western economies have experienced significant changes in the distribution of personal incomes over the last decades. The rising income inequality in the United States and in some European countries has attracted public, as well as scholarly attention.[1] Empirical and theoretical research relates income distribution and inequality to a number of social and economic outcomes, such as economic growth, international trade, health, education and criminality, to mention a few dimensions only. Despite the growing attention to the issue of income inequality in recent years, "the literature on income inequality has not typically investigated the implications of inequality operating through industrial structure" (Gulati and Ray, 2016, p. 224). In industries characterized by localized production and consumption, the provision of particular products or product variants depends not only on the size of the local market, but also on the distribution of local tastes and preferences (Waldfogel, 2008).[2] Income inequality is likely to influence the distribution and characteristics of these preferences, and may therefore be an important determinant of the varieties available on a given market.

In urban economics and economic geography, it is well-understood that densely populated urban areas can provide a larger variety of services. Glaeser et al. (2001) observe that one of the critical conditions for cities to prosper is "[f]irst, and most obviously, [...] the presence of a rich variety of services and consumer goods" (p. 28). Given the importance of these amenities, the influence of income inequality on the availability of local private goods merits further research. In a nutshell, the argument for analysing the relationship between inequality and product variety is as follows: since rich and poor consumers buy different consumer goods in different amounts, the degree of income inequality influences the size of local market demand and/or price elasticity of demand and hence the entry and product differentiation strategies of the firms. Income inequality entails heterogeneity in consumer preferences, and product differentiation is the market response to this heterogeneity.

[1] Atkinson and Bourguignon (2000) argue that "it is difficult to think of economic issues without distributive consequences and it is equally difficult to imagine problems without some allocational dimension" (p. 2). These authors, as well as D'Hombres et al. (2013), provide a detailed literature review.

[2] This is in sharp contrast to (inter)nationally traded manufactured goods, where the availability of products is virtually independent of local demand (due to e-commerce or, previously, catalogue sales) and the locations of production facilities (due to trade).

The present article contributes to the scarce empirical literature by analyzing the relationship between different measures of income inequality and firms' locations and product choices. The empirical analysis is carried out for restaurant services in Austria. Several characteristics of this industry make it particularly well-suited for this analysis. First, restaurants produce local non-tradable consumer goods (Glaeser et al., 2001, Waldfogel, 2008, Schiff, 2015) and consumers face substantial transportation costs. As a result, this industry is characterized by a large number of local markets. Secondly, product differentiation in the geographic and the characteristic space (i.e. the different locations and cuisines on offer) can be easily measured, allowing researchers to exploit spatial differences in income distribution and market structure in a cross-sectional analysis. Thirdly, the income elasticity for restaurant services is high (Aguiar and Bils, 2015) and the potential impact of the level and the distribution of income on local demand and firms' entry decisions and product choices can thus be identified more easily. Finally, data on inequality and restaurant variety are available in Austria on a fine spatial scale and we observe a substantial heterogeneity in our measures of income distribution between local markets. This variation facilitates the precise estimation of the effect of interest.

We find that inequality is positively associated with different measures of product variety: Local markets with higher income inequality are characterized by more active firms (restaurants), a larger number of different cuisines, a less concentrated distribution of available product variants, and cuisines that are on average less common. These results are robust to different local market definitions and alternative measures of income inequality. While we remain tentative in interpreting the results in a causal way, we provide sensitivity analyses suggesting that the causality (mainly) runs from income inequality to product variety.

The following section briefly reviews the existing literature and outlines the contribution of this article. Section 3 presents the most important concepts relevant for this analysis and the empirical identification strategy. Section 4 provides an overview of the datasets used in our application. The main results are discussed in Section 5 and the sensitivity analysis is provided in Section 6. Section 7 concludes.

2 Literature Review

The present analysis contributes to the literature relating market characteristics to firm location decisions, both in geographic and characteristic space. Specifically, it proposes that income inequality is important in determining the equilibrium distribution of firms, as well as their product choices.

Conceptually, we can distinguish between three main approaches to explain firms' entry and product differentiation decisions in the economics literature. In the *characteristics approach* (Lancaster, 1966, 1979), consumers are diverse and have preferences for particular product variants. Product differentiation is the market response to this consumer heterogeneity. Consumer preferences might be shaped by their different levels of income, with more affluent consumers looking for particular product variants (in horizontally differentiated markets) and willing to pay higher mark-ups for products of higher quality (in vertically differentiated markets). Gabszewicz and Thisse (1979) as well as Shaked and Sutton (1982, 1983, 1987) demonstrate theoretically that an increase in the dispersion of income within a given market results in a larger number of sellers (and thus products) in equilibrium. If consumer preferences depend on income levels, then income inequality reflects the heterogeneity in consumers' preferences, resulting in market segmentation, which decreases competitive pressure and allows more firms to enter the market. Yurko (2011) confirmes the findings of the earlier literature using a lognormal income distribution, which more closely reflects the empirical distribution of income. Her simulations demonstrate that higher income dispersion, while keeping mean income constant, results in higher product variety.

Contrary to the characteristics approach, consumers have identical preference structures in the *representative consumer approach*. However, they value variety, which motivates them to patronize multiple firms. Within this type of model, consumers buy larger quantities of each product variant if their average income increases. Faced with high income consumers, more firms will enter the market, which leads to more product variety. This is particularly relevant in the restaurant industry, a market characterized by high income elasticity: Aguiar and Bils (2015) find that spending on food away from home rises by 1.33 % for each 1 % increase in income (compared to just 0.37 % for food at home). The role of income inequality, however, has received only very limited formal attention within this theoretical framework. Monopolistic competition models in the spirit of Dixit and Stiglitz (1977) typically assume homothetic preferences (a constant elasticity of substitution (CES) utility function, for example), where aggregate demand is independent of the distribution of income (holding average income constant). If preferences are not homothetic, Foellmi and Zweimüller (2004) show that higher income inequality may lead to lower price sensitivity and higher mark-ups, allowing more firms to profitably enter the market and thus leading to more product variety.[3]

A less common approach is to assume *hierarchic consumer preferences* (see Drakopoulos, 1994, for a review of the early literature on hierarchical choice in economics). Within this framework, consumers have a hierarchy of needs, with the most basic needs being satisfied first and more advanced wants being addressed afterwards. Proponents of this approach (Jackson, 1984, Falkinger and Zweimüller, 1997, Falkinger, 1994, Falkinger and Zweimüller, 1996) therefore model preferences so that there is a fixed order of goods. While all consumers start with buying goods of the first (lowest-ranked) category and advance by buying goods of continuously higher order, consumers with lower income refrain from buying additional product variants at an earlier stage. While basic goods are therefore demanded by all consumers, advanced categories are bought by more affluent consumers only. Hierarchic preferences are most prominently used to explain structural change (Foellmi and Zweimüller, 2008, Matsuyama, 1992) and innovation activities (Zweimüller, 2000, Falkinger, 1994) in long-run growth processes, but this preference structure can also be used to relate income inequality to product variety in a single industry. For a given average income, higher inequality increases the number of consumers beyond particular threshold incomes, critical for consuming higher order products. Aggregate demand for more advanced product variants thus increases with income dispersion, as documented by Falkinger and Zweimüller (1996), allowing firms providing (higher order) niche products to profitably enter the market.

Note the close relationship between these arguments and the *central place theory*, developed by Christaller (1933) and Lösch (1944). This theory suggests a hierarchical pattern

[3]Income inequality can enter these monopolistic competition models in other ways as well: Consumers may be heterogeneous not only in their income, but also regarding their tastes for variety, as discussed in Parenti et al. (2017). If more affluent consumers value the availability of restaurant variety to a greater extent, a society with high income concentration may have a higher taste for variety at the aggregated (market) level.

among cities, such that only higher order cities offer higher order goods (like museums or universities), whereas lower order goods are provided in both high and low order cities.[4] While central place theory describes this *hierarchy principle* for different goods, Mori et al. (2008) and Hsu (2012) find similar patterns when investigating the industrial composition in Japan and the United States, respectively. If industries are located in a larger number of cities, the average size of the cities hosting these industries declines (in a log-linear way). According to our knowledge, Schiff (2015) is the first to relate the central place theory to product variety within a specific industry. Higher order cities host a larger population, and aggregate demand is therefore sufficiently large, such that even firms offering niche products can profitably enter the market. Larger markets are thus not only characterized by more (differentiated) products, but also by offering rare (in addition to common) product variants. Although Schiff (2015) does not address income inequality explicitly in his analysis, aggregate demand may differ between cities of similar size (i.e. of similar hierarchy) due to differences in the income distribution, as discussed previously, leading to differences in product variety even between cities of the same size.

While the theoretical literature suggests that higher income inequality is likely to lead to markets offering a larger variety of products, including also less common product variants, empirical research on the role of the income distribution in determining the industry structure is scarce. We know from empirical research using individual household data that households with higher income consume a larger variety of products, regarding both food items (Thiele and Weiss, 2003)[5] and other commodities (Jackson, 1984). However, it is difficult to draw general conclusions from these results regarding the relationship between inequality and product variety at an aggregated (market) level. Consistent with the findings based on household data, Behrman and Deolalikar (1989) and Theil and Finke (1983) provide evidence for a positive relationship between the level of per-capita income and the availability of product variety based on cross-country studies, but do not include measures of income dispersion in their analyses. One of the very few exceptions in this regard are Falkinger and Zweimüller (1996, 1997), who document a positive relationship between the

[4] Hsu (2012) provides a parsimonious model that formalizes this theory.

[5] A detailed review of this literature is available in Weiss (2011).

degree of income inequality and product variety. These studies, however, are carried out on the basis of highly aggregated regional data (country level data) and a broad categorization of products only.

The empirical approach used here is most closely related to Schiff (2015), who presents empirical evidence on product variety in U. S. cities. Based on data for 127,000 restaurants across 726 cities in the U. S., the author observes that larger cities host both less common as well as a larger number of different cuisines. Schiff (2015) finds a significant effect of geographic concentration of population, age structure, ethnic diversity and average household size on the variety of restaurants and cuisines. Median household income does not contribute significantly to the explanatory power of the models estimated. As in many other empirical studies in regional, urban and industrial economics, the effects of income distribution and income inequality are not investigated.[6] The present article contributes to this literature by explicitly focusing on the impact of income inequality on product diversity.

3 Conceptual Framework and Identification

As argued by Glaeser et al. (2001), "restaurants [...] are hard to transport and are therefore local goods" (p. 28). For local private goods we can expect a strong relationship between market structure and the provision of restaurant services in a local market.[7] We investigate the relationship between income distribution and market conduct by estimating the following regression at the local market level:

$$V_i = f(\, \alpha + \beta \; INEQ_i + \gamma \; \overline{INC}_i + \boldsymbol{X}_i \boldsymbol{\delta} \,), \tag{1}$$

with the endogenous variable V_i as an indicator of product variety of local market i. The variables $INEQ_i$ and $\overline{INC}_i$ capture income inequality and average income. The row vector $\boldsymbol{X}_i$ contains a number of control variables at the local market level. α, β, γ and $\boldsymbol{\delta}$ are the

[6] While this literature establishes a number of benefits for businesses located in large markets, it pays little attention to the role of income inequality in determining the equilibrium mix of varieties supplied. Glaeser (2010) provides an overview of the economic literature on agglomeration effects.

[7] Empirical articles relating demand and supply of locally produced and consumed goods and services include contributions on diverse industries such as restaurants (Waldfogel, 2008), child care services (Pennerstorfer and Pennerstorfer, 2019) and local media (George and Waldfogel, 2003, 2006, Waldfogel, 2003).

(vectors of) parameters to be estimated, with β as the main coefficient of interest. Depending on the properties of the endogenous variable V_i, equation (1) will be estimated by a negative binomial or a Poisson regression model (with the function $f(\cdot)$ as an exponential function in these cases), or via OLS.

A potential problem in identifying the causal effect of income distribution on the local supply of restaurants is migration between markets. Glaeser et al. (2001) argues that cities which host a larger variety of consumer goods and services tend to experience higher population growth. In other studies, the provision of public goods (Tiebout, 1956), the availability of a large variety (Stahl, 1983) or appealing variants of private goods (Waldfogel, 2008) are also put forward as economic rationales for sorting of individuals across neighborhoods. This would imply that the size and the distribution of population and thus our measures of average income and income inequality are influenced by restaurant variety (reverse causality).

However, we expect the effect of restaurant variety on individuals' residential mobility to be rather small, as restaurants are only one of many locally produced and consumed goods and services. Empirical evidence suggests that local employment opportunities are more important than local amenities for households with (potentially) economically active persons (see Chen and Rosenthal, 2008, Scott, 2010).[8] Further, even if local restaurant variety attracts individuals of a particular income segment, its influence on income inequality is ambiguous and depends on the income distribution of the original residential population.

We nevertheless provide two attempts to address the issue of causality in the empirical analysis. First, we lag the explanatory variables measuring the income distribution at intervals of about three years throughout the analysis. Data on income and education are collected for the years 2013 and 2014, respectively, while information on restaurants is obtained between November 2016 and March 2017 (more details on the data will be provided in the following section).

Second, we split the sample based on gross migration rates. If migration biases our parameter estimates, this bias will be smaller if migration rates are low. To outline the intuition of this approach, assume that residential mobility depends only on differences in

[8]Note that there is hardly any regional variation in taxes in Austria, so the mechanism that high-income households self-select into low-tax jurisdictions, as documented by Schmidheiny (2006) for Switzerland, does not apply to our sample region.

amenities across local markets and on moving costs, i.e. costs of leaving the old community and settling in the new one. The estimated relationship between income inequality and the local supply of restaurants, $\hat{\beta}$ in equation (1), could be interpreted causally, running from income distribution to restaurant variety, if moving costs are prohibitively high. If moving costs decline, residential mobility grows and the individuals' location choices depend increasingly on differences in amenities across local markets. The (absolute size of the) bias in the estimated parameter $\hat{\beta}$ should therefore depend negatively on mobility costs.

While the extreme case of prohibitively high moving costs is unlikely, empirical evidence suggests that moving costs differ substantially between individuals, but also between neighborhoods. One potential source of moving cost differences is variation in home ownership rates. Moving costs are found to be higher for homeowners compared to renters, and empirical results provided by Henley (1998), Oswald (1996), Broulíková et al. (2020), Munch et al. (2006) and Wolf and Caruana-Galizia (2015) show that homeowners are indeed less mobile. There are large regional differences in home ownership rates in Austria, ranging form 17 % to 76 % even after aggregating to the level of NUTS-2-regions (OECD, 2008, p. 140).[9] Similarly, settlement costs are expected to be lower if the destination neighborhood offers many rental opportunities. Differences in (gross) migration rates between neighborhoods, originating from different home ownership rates (or from various other sources), should reflect this regional heterogeneity in moving costs.

In regions with lower (gross) migration rates, moving costs are expected to be higher.[10] In these areas, reverse causality is less likely to occur and the potential bias of the estimated parameter $\hat{\beta}$ should be smaller. In a sensitivity analysis (Section 6), we therefore split the sample based on residential mobility rates. We find similar results for different sub-samples, suggesting that the potential bias is small and causality runs (mainly) from the local income distribution to restaurant variety. However, we acknowledge that the differences in moving costs, manifested in regional heterogeneity in residential mobility, are not necessarily orthogonal to restaurant variety, and therefore remain tentative in asserting the causal interpretation

[9] The regional variation in home ownership rates in Austria is substantial and larger than in any other OECD country (OECD, 2008). Note that the variation in our sample is expected to be much higher, as we draw on 2,376 municipalities rather than the 9 NUTS-2-regions.

[10] We find large differences in residential mobility in Austria. Gross migration rates in the 95$^{\text{th}}$ (90$^{\text{th}}$) percentile are 3.3 (2.4) times larger than the 5$^{\text{th}}$ (10$^{\text{th}}$) percentile.

of our results.

4 Market Definition and Data

4.1 Local Market Definition

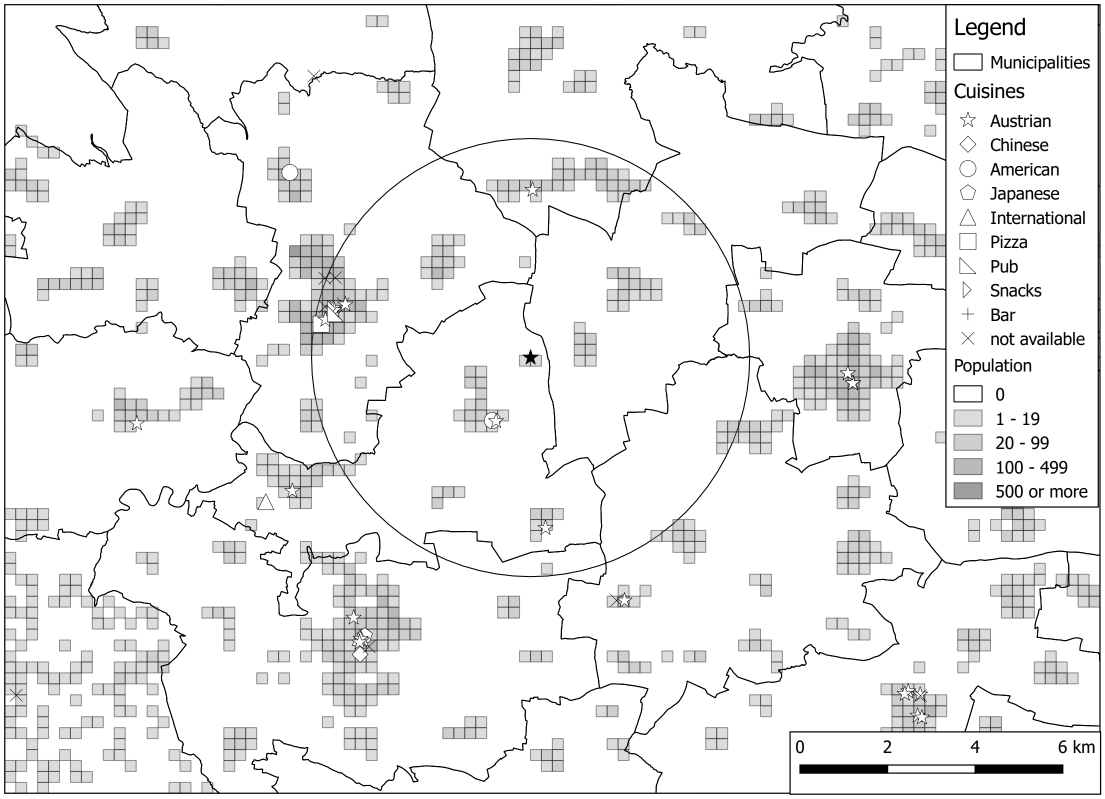
To analyse the relationship between income inequality and firms' product differentiation strategies, we exploit spatial variation in the number and the identities of firms, as well as inequality levels across a large number of local markets in Austria. We use two concepts to delineate local markets. First, we use municipal boundaries. The use of administrative entities as local markets is very common when analyzing market conduct (for applications in the restaurants industry, see Waldfogel, 2008 and Berry and Waldfogel, 2010).

In an alternative approach, we define a local market for each restaurant by drawing a circle around its geographic location. To calculate measures of product variety, we use information on all restaurants within a particular radius.[11] This approach is very flexible and allows local markets to be defined uniformly across space. Furthermore, the market delineation is not influenced by administrative authorities, who regularly create regional entities of differing sizes. We use a radius of five kilometers to define local markets in the main specification. Smaller (0.5 km and 2 km) and larger (10 km) distance bands are used in the sensitivity analysis. Table A.1 in the appendix demonstrates that inequality measures based on different threshold distances are highly correlated (between 0.64 and 0.94).

An illustration of the two market delineation techniques, as well as the density of firms and residential population at a level of 250×250 meter grid cells, is provided in Figure 1 for a sample area.

[11] The idea of constructing local markets around each supplier dates back to Shepard (1991). It is common to count the number of firms within a threshold distance, in particular to derive indicators of the intensity of local competition. Using this approach to calculate demand indicators is less common, probably due to a lack of data. Empirical contributions by Seim (2006), Zhu and Singh (2009), Datta and Sudhir (2013), Nishida (2015) or Pennerstorfer and Pennerstorfer (2019) are notable exceptions.

Figure 1: Restaurants, municipalities and circular markets



Notes: The circle shows the local market with a radius of 5 km for the restaurant indicated by a black star. Black lines denote municipal boundaries.

4.2 Restaurants and Product Variety

Data on restaurants were obtained from the online review sites Tripadvisor.com and Restauranttester.at between November 2016 and March 2017. Tripadvisor is an international rating website for restaurants, hotels and other activities that are of interest to travellers. Restauranttester is an Austrian restaurant rating website, which caters predominantly to locals or at least to those consumers who have a good command of the German language. Due to these differences, Tripadvisor is more prevalent in cities and tourist destinations, while Restauranttester covers more restaurants in rural areas. The datasets were matched to generate an exhaustive picture of the Austrian restaurant market. The total count of restaurants is 24,460, which has been cross-validated with data from the Austrian Chamber of Commerce.[12]

[12] All Austrian companies are obliged by law to become members of the respective branch of the Austrian Chamber of Commerce. The Chamber can thus provide a complete and up-to-date list of all restaurants in Austria.

The dataset includes information on the precise locations of all observations (addresses and geographic coordinates), as well as their specific product varieties (cuisine types).

We use a number of measures of product variety applied in the empirical literature (see e.g. Schiff, 2015). In both Dixit and Stiglitz (1977)-type as well as Lancasterian (Lancaster, 1966, 1979) models of monopolistic competition, each firm produces a unique variant of the product. The number of different products would thus be represented by the *number of restaurants* (NR) in a local market.

Counting the number of restaurants assumes that product varieties are "symmetric" in the sense that every variety is valued equally by consumers: only the number of restaurants is important, irrespective of their identities. Consumers may end up with a selection of very similar products, as the number of restaurants provides no information on the range within the product space covered by these differentiated products. We therefore follow Schiff (2015) and take the *number of different cuisines* (NC) as our second measure of product variety. Cuisines can be considered as relevant subcategories of restaurants, and this measure thus comprises some information on the degree of product differentiation.

Following Schiff (2015), we use the restaurants' primary cuisines, i.e. the first cuisine listed on the respective website. In case of conflicting primary cuisines reported by the two data sources we stick to the categorization of Tripadvisor. The sample contains 100 different cuisine types with "Austrian" as the most common one, offered by 8,287 restaurants (34 %) in 1,478 different municipalities. A list of the ten most and least common cuisines is reported in Table A.2 in the appendix. For about one fifth of all restaurants no cuisine type is listed.[13] These establishments are classified as selling an "unknown" product type.[14]

[13]Mazzolari and Neumark (2012) distinguish between fifteen different ethnic cuisines in their original dataset and do not have a cuisine type information for 40 % of their data. To remedy this missing data problem, they re-classify their data searching for words in the restaurant names that would indicate their cuisine type (e.g. "Chinese") which reduces the missing cuisine types to 20 % and increases the number of different cuisines to 18. Shoag and Veuger (2019) measure restaurant diversity by identifying 28 different cuisine types while Schiff (2015) distinguishes between 90 different cuisines.

[14]To calculate measures of product variety, the cuisines of these restaurants are assumed to be distributed in the same way as the cuisines of those restaurants in a local market, where this information is available. If, for example, a market hosts five restaurants, with two offering Austrian, one Italian and two "unknown" cuisines, we assume that 3.33 restaurants in this market offer Austrian and 1.67 provide Italian cuisine. If all cuisines in a local market are unknown, these restaurants are assumed to offer Austrian cuisine. In a sensitivity analysis, unknown cuisines are treated as Austrian restaurants when calculating measures of product variety.

The number of different cuisines neglects information on the distribution of restaurants among the available product types. The variety in a market may be perceived as lower if there are e.g. five Burger and one Chinese restaurants, relative to a market with three restaurants of each subcategory. To generate a measure of product variety that incorporates this aspect, we therefore compare each market i with a hypothetical benchmark market b, where each of the C cuisines available in Austria exists exactly once. We then calculate an index of angular separation in the vein of Jaffe (1986), taking into account both the number and the frequency of distinct cuisines in a market. This measure, denoted as *horizontal variety* (HV), is defined as follows:

$$HV_i = \frac{\sum_{c=1}^{C} s_{cb} s_{ci}}{(\sum_{c=1}^{C} s_{cb}^2)^{1/2} (\sum_{c=1}^{C} s_{ci}^2)^{1/2}} = \frac{1}{C^{1/2} (HHI_i)^{1/2}}$$

The shares of cuisines s_{cb} and s_{ci} are defined as the number of restaurants offering a particular cuisine c divided by the total number of restaurants in the benchmark market b and market i, respectively. The HV index of a local market takes into account the concentration of cuisines within the market, with less concentration resulting in higher levels of variety. It can take values between $\frac{1}{C^{1/2}}$ (if all restaurants offer the same cuisine) and 1 (if the local market resembles the benchmark market).[15] The index is undefined in markets without any restaurant and the respective markets have to be excluded from the empirical analysis when focusing on this measure of product variety.

Note that the HV index does not explicitly take into account whether the cuisines available in a particular market are more or less common, i.e. whether they are available in many other markets. Consumers, however, might value the availability of a rare product higher than products that are easily available in many markets, as this signals novelty and, potentially, higher status.[16] A "hierarchical" approach to product variety requires the exact

[15] Alternative measures, like the Berry (1971)-index or entropy indices, also depend on the market shares of the available product variants and are thus similar to our measure of horizontal variety (HV). See Drescher et al. (2008), Thiele and Weiss (2003) and Weiss (2011) for a detailed discussion.

[16] This idea goes back to Veblen (1899), who emphasized the importance of social status demonstrated by the 'conspicuous consumption' of scarce objects. More recently, Koford and Tschoegl (1998) review several theories of demand arguing that consumers value rarity. They cite a psychological study (Worchel et al., 1975), in which experimental subjects found scarce cookies more desirable than abundant ones. A detailed discussion of the concept of rarity in an ecological context (species rarity), its measurement as well as its relationship to diversity is provided in Patil and Taillie (1982).

identities of the available varieties in a local market to be taken into account. We follow Schiff (2015) and define a measure of *average rarity* (R). For each cuisine c we count the number of local markets where this cuisine is available. These are called choice cities, denoted by CC_c. CC_{max} indicates the number of choice cities for the most common cuisine. Based on these two variables we calculate an indicator of the relative rarity of each cuisine: $r_c = CC_{max} - CC_c$. Our measure for the average rarity of the cuisines available in market i is then defined as:

$$R_i = \frac{\sum_{c=1}^{C} D_{ci} r_c}{\sum_{c=1}^{C} D_{ci}},$$

with the dummy variable $D_{ci} = 1$ if cuisine c is available in market i, and zero otherwise. Again, this index is undefined in markets without any restaurant.[17]

Table 1 provides a simple example to illustrate how the different indices reflect the distribution of products in a market. The "benchmark case" represents a local market in which all four cuisines (A, B, C and D) are observed exactly once. Panel I shows how the indices are affected by changes in the numbers of cuisines. In this panel, each cuisine occurs at most once in each local market, which is why the number of restaurants (NR) is equal to the number of cuisines (NC). The lack of concentration of restaurants in one cuisine type also explains why the measure of horizontal variety (HV) tracks the number of cuisines closely—it is largest in the benchmark market and smallest in the markets with just one restaurant. This correspondence between the number of cuisines and horizontal variety is not present in the measure of cuisine rarity (R). As can be seen in Panel I, market 4 has a low score in terms of NR and HV. This is intuitive, since there is only one restaurant in that market (offering cuisine D). However, cuisine D is relatively rare (it is offered only in the benchmark market in addition to Market 4). This results in a very high measure of the rarity index, despite the low score along all other variety dimensions. It demonstrates that while other dimensions of product variety are likely to be larger in urban markets, high rarity levels are also possible in small markets.

Panel II of Table 1 illustrates the difference between the measure of horizontal variety and the number of cuisines. While the HV index rewards markets with a higher number of

[17] The index of average rarity, R_i, is scaled by 1/1,000 in the empirical analysis to facilitate the exposition of the regression results.

Table 1: Product distributions and measures of variety

Panel I: fixed frequency of cuisine offers

Cuisine	A	B	C	D	NR	NC	HV	R
Benchmark Case	■	■	■	■	4	4	1.00	1.25
Market 1	■				1	1	0.50	0.00
Market 2	■	■			2	2	0.71	0.50
Market 3	■	■	■		3	3	0.87	1.00
Market 4				■	1	1	0.50	2.00
Choice cities	4	3	2	2				
Cuisine rarity	0	1	2	2				

Panel II: fixed number of restaurants

Cuisine	A	B	C	D	NR	NC	HV	R
Benchmark Case	■	■	■	■	4	4	1.00	1.50
Market 1	■ ■ ■ ■				4	1	0.50	0.00
Market 2	■ ■ ■	■			4	2	0.63	0.50
Market 3	■ ■	■ ■			4	2	0.71	1.00
Market 4				■ ■ ■ ■	4	1	0.50	2.00
Choice cities	4	3	1	2				
Cuisine rarity	0	1	3	2				

distinct cuisines, it penalizes repetitions of the same cuisine. This leads to a lower horizontal variety score for market 2 (which hosts three restaurants with cuisine A and one with cuisine B) compared to market 3 (where the distribution is more equal). Panel II also demonstrates the sensitivity of the rarity measure R to the number of available cuisines in all other markets. Note that the index value for a particular market depends on the number of available cuisines in all markets. See in particular the benchmark market in Panel I and Panel II in Table 1. In Panel I two markets offer cuisine C, whereas in Panel II this cuisine is only available in the benchmark market, leading to an increase in the rarity measure from 1.25 to 1.50.

4.3 Inequality

To calculate measures of inequality at the local market level, we use data on income and information on education. Information on formal education is utilized because it is available at a finer spatial scale.[18] In both cases, we apply different indicators of inequality for a number

[18]The high correlation between formal education and income is well-documented in the literature, both because education causally affects income, and because education may be correlated with individuals' abilities

of reasons: (i) Although ways to measure inequality adequately have been the subject of a lively debate for some time (see in particular early contributions by Persons, 1909, Dalton, 1920, Schutz, 1951, and Atkinson, 1970), no consensus has emerged in the literature on a single measure of inequality. (ii) Some indices are sensitive to particular segments of the distribution (see Moser and Schnetzer, 2017, for a discussion). The empirical results might thus depend on the choice of the inequality measure, if some segments (affecting a specific inequality measure strongly) have a particularly large/small influence on demand for restaurant services. (iii) Different measures of inequality also allow us to come closer to the concepts used in the theoretical literature and address the question of whether the support (range) of the distribution (as, e.g., in Shaked and Sutton, 1982, 1983) or the distribution within this interval (as modeled by Yurko, 2011) is particularly important for firms' product differentiation choices.

We apply the well-known Gini index in our main specifications and use Theil and Atkinson indices (see Allison, 1978, for an overview) in the sensitivity analyses. These indices depend on the level of income and formal education of all individuals in a local market. To proxy the sample range we include the ratios between the 90^{th} and the 10^{th} percentile (90/10) and between the 80^{th} and the 20^{th} percentile (80/20).[19] Furthermore, we distinguish between differences in the upper and the lower tail of the distribution by considering the 90/50 and the 50/10 quantile ratio. When using data on education we convert information on the individuals' highest educational attainments into years of schooling and calculate the same measures of inequality.

(a) Income Inequality

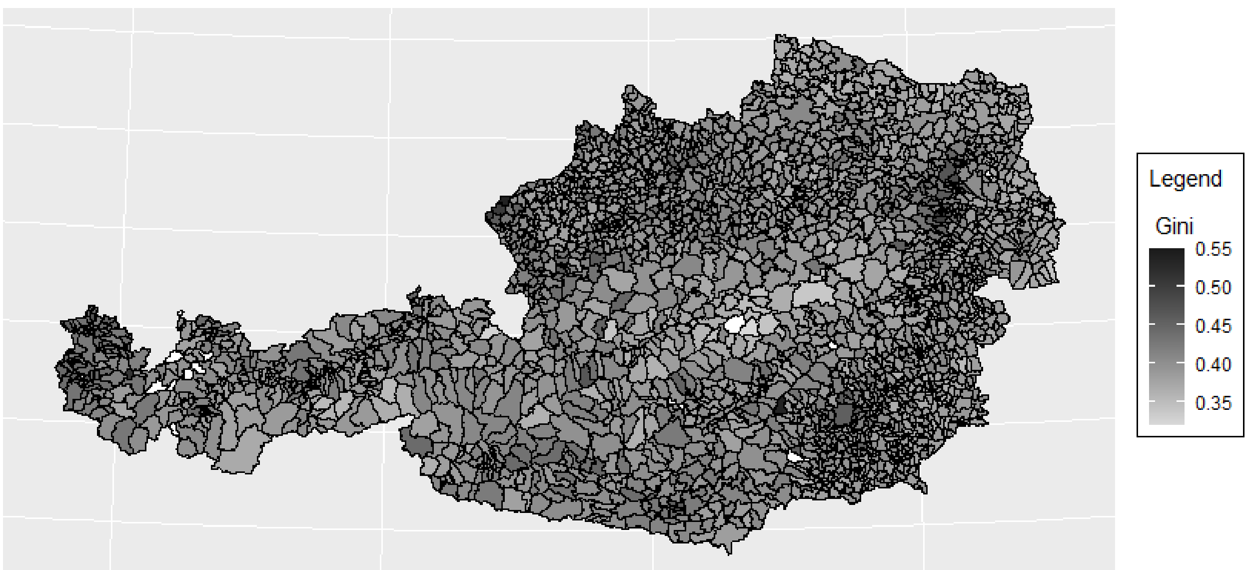
To calculate measures of income inequality, we can draw on information on gross wages derived from tax data, collected by Statistics Austria for the year 2013. The income distribution is observed at the individual level for the entire Austrian population, except self-employed individuals. Annual gross wages are calculated as all earnings received within this year and include supplementary payments and social security contributions. This data covers about

or skill levels (characteristics that also influence income). See, for example, Card (1999), Hanushek and Woessmann (2008) and Krueger and Lindahl (2001) for comprehensive surveys.

[19]Note that the range of the income distribution is not available due to privacy concerns.

6.5 million individuals, accounting for approximately 90 % of all tax payers (the remaining 10 % are self-employed). Income inequality measures are calculated at the municipal level.[20] Austrian municipalities are small regional units, covering 35 km^2 and hosting 2,431 inhabitants on average. Spatial heterogeneity in income inequality between municipalities is large. Income inequality as measured by the Gini index is illustrated in Figure 2. The ratio between the 90^{th} and the 10^{th} income percentile at the municipal level ranges from 7 to 14 (not taking into account the outlier municipalities with the highest and lowest 5 % of values). This is illustrated in Figure 3.

Figure 2: Gini coefficient at the municipal level in Austria

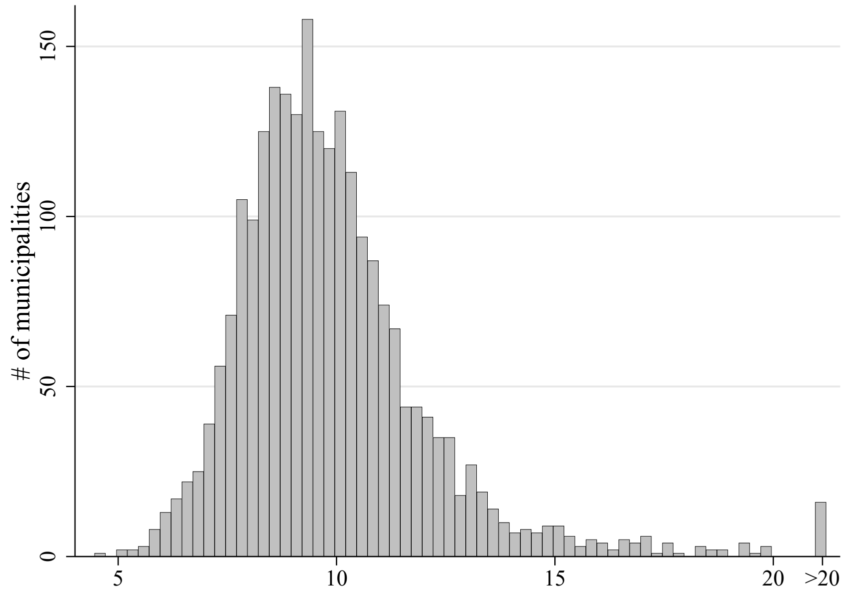


Notes: Gini coefficients based on income data from 2013. Due to data privacy restrictions, the Gini coefficient is not available for municipalities with less than 100 inhabitants, which is the case for 19 municipalities. Those municipalities are colored in white.

Table 2 shows the correlation between different inequality measures. While all variables are clearly positively related, the correlation between the Gini, Theil and Atkinson indices is particularly high (≥ 0.91). The co-movement of these dispersion measures and the quantile ratios 90/10, 80/20, 90/50 and 50/10 are somewhat lower (between 0.50 and 0.79). Interestingly, the 90/10 ratio is more strongly correlated with the 50/10 ratio (0.96) compared to the 90/50 ratio (0.62).

[20]We are thankful to Mathias Moser for sharing these data with us. Due to privacy issues, we are not allowed to use information from municipalities with less than 100 inhabitants, which reduces the sample size by 19 (out of 2,379) municipalities.

Figure 3: Heterogeneity in income inequality across Austrian municipalities



Notes: Histogram depicts the distribution of the ratio between the 90$^{\text{th}}$ and the 10$^{\text{th}}$ income percentile at the municipal level (N = 2,360) for the year 2003.

Table 2: Correlation between measures of income inequality at the municipal level (N = 2,360)

		Dispersion indices			Quantile ratios			
		Gini	Theil	Atkinson	90/10	80/20	90/50	50/10
Dispers. indices	Gini	1						
	Theil	0.910	1					
	Atkinson	0.980	0.948	1				
Quantile ratios	90/10	0.750	0.582	0.769	1			
	80/20	0.685	0.501	0.682	0.882	1		
	90/50	0.790	0.606	0.709	0.623	0.577	1	
	50/10	0.628	0.486	0.677	0.956	0.814	0.389	1

(b) Educational Inequality

While income inequality is measured at the municipal level, information on educational inequality is available on a finer scale. Information on the residential population and their highest educational attainments (8 categories) is provided by Statistics Austria at the level of 250 m × 250 m grid cells for the year 2014. These regional statistical grid units are placed over the entire territory of Austria and are independent of administrative boundaries (see

Figure 1).[21]

For each of the eight levels of educational attainments available in the data we assign years of schooling using a country-specific conversion table for Austria provided by the OECD (2013). Using this information, we calculate mean years of schooling as well as the aforementioned inequality measures based on all individuals aged 15 years or older who reside within the radius drawn around each restaurant.[22]

The correlation between different indices of inequality based on years of schooling is reported in Table 3. Compared to inequality measures based on wage income, the correlation coefficients in Table 3 are larger. Only the 50/10 quantile ratio is weakly correlated (between 0.14 and 0.28) with all other measures. This is because we observe little variation in the 50/10 quantile ratio, with more than 95 % of all local markets reporting a ratio of 1.5.

Table 3: Correlation between measures of educational inequality using circular markets ($N =$ 24,424)

		Dispersion indices			Quantile ratios			
		$\text{Gini}_{\text{Educ}}$	$\text{Theil}_{\text{Educ}}$	$\text{Atkinson}_{\text{Educ}}$	90/10	80/20	90/50	50/10
Dispers. indices	$\text{Gini}_{\text{Educ}}$	1						
	$\text{Theil}_{\text{Educ}}$	0.996	1					
	$\text{Atkinson}_{\text{Educ}}$	0.996	0.999	1				
Quantile ratios	90/10	0.851	0.842	0.846	1			
	80/20	0.800	0.812	0.824	0.670	1		
	90/50	0.851	0.840	0.842	0.989	0.667	1	
	50/10	0.184	0.191	0.199	0.278	0.159	0.140	1

Note: Correlations are based on local markets defined by a radius of 5 km around each restaurant.

Finally, we also calculate the respective variables on the distribution of education (years of schooling) at the municipal level and compare them with the indicators of the income distribution. The correlation between mean income and the average years of schooling is high (0.76). As expected, measures of inequality are positively correlated (with a correlation coefficient of 0.35 for the Gini indices, for example).

[21] Educational attainments are not reported if the residential population is three or less, due to privacy concerns. About 1 % of the population is affected by this data restriction.

[22] If cells are only partly located within the threshold distance, the population is considered to be within the local market as long as the centroid of the respective grid cell lies within the critical distance.

4.4 Control Variables

In addition to income or education inequality of the residential population, we include a number of variables affecting demand at the local market level provided by Statistics Austria (unless explicitly stated otherwise). We classify these indicators as either measures of demand heterogeneity or demand shifters.

We include the size (area) of a municipality as a potential proxy for demand heterogeneity. If a local market covers a large area, restaurants can spatially differentiate from their competitors, which might allow more restaurants to enter in equilibrium while reducing the need to differentiate in other dimensions (e.g. cuisine type). We further control for ethnic diversity, as a more ethnically heterogeneous population is expected to have a more diverse demand structure (an aspect emphasized for the restaurant industry by Davis et al., 2019, Mazzolari and Neumark, 2012, and Waldfogel, 2008). Foreign-born individuals might have a higher preference for their national food and are provided with the skills to open up a restaurant offering this cuisine. Using data from 2013, we calculate the inverse of the Herfindahl-Hirschman Index (HHI) based on the nationalities of all residents, so that the measure increases with ethnic diversity. The data distinguishes between 207 different source countries of the residential population for each municipality.

The most important demand shifters included in the empirical specification are mean income (or the average years of schooling to proxy income) and population size. These variables are expected to increase demand and thus the number of restaurants as well as the number of cuisines. Regarding the average rarity of the cuisines available, Schiff (2015) argues that very rare cuisines should be present only in big and dense cities, and high demand should therefore make the available cuisines less common on average. In addition to the residential population, the empirical specifications also include information on commuting patterns, as regular commuters may consume restaurant services close to their workplace locations. We expect to find a positive relationship between in-commuters and the measures of product variety, but opposing results for out-commuters. Data on the population size and on commuting patters are provided at the municipal level for the year 2015. Furthermore, all model specifications include a variable on tourism, measured as the number of overnight stays between November 2014 and October 2015. Tourists should have a large influence on demand, as they often do not have access to facilities which would allow them to prepare food themselves, and are therefore very likely to patronize restaurants.[23]

Additionally, we include the average household size (from 2016), as for larger households cooking at home could be cheaper due to economies of scale. As Waldfogel (2008) shows, demographic characteristics of the population influence what variety of restaurants is offered in a local market. We thus include the population shares from 2013, grouped in six different age cohorts with the youngest group (residents younger than 15 years old) as the reference group. We expect that residents in their prime working age have a larger demand than younger or older cohorts. Another factor that might drive demand for restaurants are shopping areas. In larger malls or shopping streets in Austria there is typically an H & M store present. We include a count measure for all H & M stores in the local market to proxy the presence of shopping areas.[24]

Finally, we use migration patterns from 2013 to construct indicators of moving costs (see the discussion in Section 3), and operationalize this concept by calculating gross migration rates—computed as (immigration + emigration)/population—as well as the minimum of immigration and emigration rates.[25] Summary statistics on all variables used in the analysis are presented in Table A.3 (for municipalities) and in Table A.4 (for circular markets).

When using threshold distances to define local markets around each restaurant we can draw on information on the residential population and their educational attainments, provided at the grid cell level, and on the exact locations of H & M stores. All other variables are available at the municipal level only. The values of these control variables are based on the municipality where the restaurant in the middle of the respective circular market is located.

[23]Information on overnight stays has to be reported to Statistics Austria by all municipalities with more than 1,000 overnight stays per year. This statistic thus documents more than 99 % of all overnight stays in Austria. For municipalities with less tourism we do not know the exact number of overnight stays and set the respective figure to unity.

[24]The data on these stores was retrieved from H&M.com on February 12$^{\text{th}}$ 2019 and geocoded according to their addresses.

[25]We use population data from 2011 to calculate migration rates, so that migrant flows do not mechanically affect the denominator of these ratios. Migration flows comprise both internal and external migrants.

5 Main Results

To analyze the relationship between income inequality and product variety, we report regression results on all four different measures of product variety in each result table. We use negative binomial models to explain the number of restaurants (NR) and Poisson models to analyze the number of cuisines (NC), while we apply OLS for the measures of horizontal variety (HV) and average cuisine rarity (R).[26] In a first step, inequality is measured by the Gini index. Regression results based on municipal markets are reported in Table 4, and parameter estimates relying on circular markets based on a threshold distance of 5 kilometers are summarized in Table 5.

Using municipal markets, Table 4 reveals that income inequality measured by the logarithm of the Gini index is positively and significantly correlated with all measures of product variety, namely with the number of restaurants (Model [1]), the number of different cuisines (Model [2]), the horizontal variety (Model [3]) and the average rarity of the cuisines offered (Model [4]). The positive coefficient for the Gini index in regression [3] indicates that the mix of cuisines on offer is less concentrated when income inequality is larger. The relationship between inequality and rarity is positive, but statistically significant at the 10 % significance level only (column [4]). This indicates that income concentration not only raises the total number of restaurants and cuisines, but also increases that of cuisines that are less common disproportionately. Markets with high degrees of income inequality are thus characterized by a distribution of cuisines that is less concentrated (model [3]) and includes less common cuisines (column [4]). Note that the average income is positively associated with the number of restaurants and cuisines, but not significantly related to the concentration or the rarity of the cuisines offered in a local market.

To illustrate the magnitude of these effects, we visualize the predicted number of restaurants and cuisines for different values of inequality, while restricting all other variables to

[26] Since the number of restaurants and the number of cuisines are count measures, we employ a negative binomial and a Poisson regression model. The decision for the negative binomial regression model over the Poisson model or vice versa was made after performing a likelihood-ratio test and analysing the Akaike and Bayes information criteria, using the Long and Freese's (2014) "countfit" command in STATA. These tests suggest that the negative binomial model is a better fit for the variable number of restaurants and its dispersed distribution, while a Poisson specification is appropriate when the number of cuisines is used as the dependent variable.

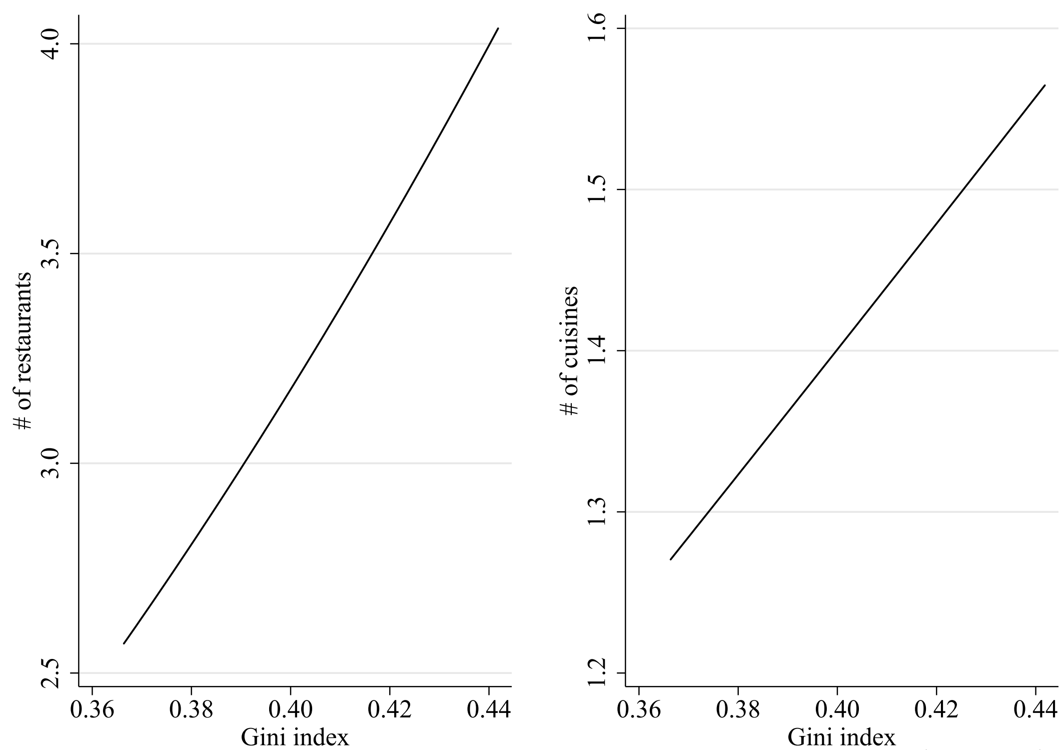
Table 4: Regression results on product variety based on municipal markets

Dependent variable	Model [1] # restaurants	Model [2] # cuisines	Model [3] HV	Model [4] Rarity
Gini index (in log)	2.410 ***	1.112 ***	0.031 **	0.428 *
	(0.376)	(0.249)	(0.012)	(0.225)
Mean income (in log)	0.992 ***	0.756 ***	0.005	0.058
	(0.252)	(0.173)	(0.008)	(0.151)
Area (in log)	0.109 ***	0.013	−0.005 ***	−0.029 *
	(0.025)	(0.017)	(0.001)	(0.015)
Ethnic diversity	1.280 ***	0.496 ***	0.046 ***	0.352 ***
	(0.208)	(0.104)	(0.006)	(0.116)
Population size (in log)	2.498 ***	1.965 ***	0.067 ***	0.490 **
	(0.304)	(0.217)	(0.011)	(0.194)
Tourism (in log)	0.111 ***	0.071 ***	0.002 ***	0.028 ***
	(0.005)	(0.005)	(0.000)	(0.003)
In-commuters (in log)	0.354 ***	0.303 ***	0.006 ***	0.127 ***
	(0.036)	(0.024)	(0.001)	(0.020)
Out-commuters (in log)	−2.286 ***	−1.823 ***	−0.055 ***	−0.436 **
	(0.293)	(0.208)	(0.010)	(0.189)
Average household size (in log)	−0.364	−0.722 ***	−0.009	−0.249
	(0.336)	(0.267)	(0.011)	(0.195)
Share population aged 15-29	2.565	3.848 ***	0.314 ***	1.805
	(1.915)	(1.263)	(0.062)	(1.132)
Share population aged 30-44	11.366 ***	9.141 ***	0.511 ***	4.826 ***
	(2.237)	(1.595)	(0.073)	(1.332)
Share population aged 45-59	7.678 ***	5.707 ***	0.238 ***	3.241 ***
	(1.563)	(1.256)	(0.052)	(0.939)
Share population aged 60-74	5.724 ***	3.682 ***	0.206 ***	1.832 *
	(1.709)	(1.360)	(0.055)	(1.001)
Share population aged $\geq$ 75	1.398	0.510	0.223 ***	0.722
	(1.702)	(1.297)	(0.055)	(0.993)
# H & M stores (+1; in log)	0.250 *	0.017	0.049 ***	−0.051
	(0.136)	(0.051)	(0.005)	(0.089)
Constant	−19.748 ***	−15.358 ***	−0.375 ***	−3.866 **
	(3.038)	(2.176)	(0.101)	(1.834)
Observations	2,360	2,360	1,876	1,876
Pseudo R^2	0.215	0.525		
R^2			0.586	0.319
Method	Negative binomial	Poisson	OLS	OLS

Notes: Standard errors are reported in parentheses. *** significant at 1 %, ** significant at 5 %, * significant at 10 % level.

their sample means. The estimated relationship is depicted in Figure 4, with the Gini index (in levels) going from the 5th to the 95th percentile. Within this range of income inequality the expected number of restaurants increases from 2.57 to 4.04 (+57 %) and the expected number of different cuisines from 1.27 to 1.56 (+23 %), suggesting that these relationships are economically meaningful, in addition to being statistically significant. The effects on horizontal variety and rarity are smaller, as a one standard deviation increase in the log of the Gini index is associated with an approximate 0.04 standard deviation higher value for each of these two endogenous variables.

Figure 4: Predicted number of restaurants and cuisines in municipal markets



Notes: The figures illustrate the change in the expected number of restaurants (left panel) and in the expected number of different cuisines (right panel) in a local market due to variation in the Gini index, based on the parameter estimates reported in Model [1] and Model [2] of Table 4, respectively. The Gini index varies from the 5th to the 95th percentile, while all other explanatory variables are set to their sample means.

Additional variables indicating the heterogeneity in demand include the municipality's area and its inhabitants' ethnic diversity. A larger area is positively associated with the number of restaurants, but negatively with horizontal variety and average cuisine rarity. If the same number of inhabitants (included as a control variable in all model specifications) is dispersed over a larger area, more restaurants can profitably enter the market, because there is more room to spatially differentiate. This leads to cuisine duplication, leaving the number of cuisines constant while depressing the value of horizontal variety and cuisine rarity. Furthermore, the results suggest that in markets with a more diverse ethnic structure more varieties are offered, with significant estimates for all four measures of product variety.

Most of the other coefficients indicating potential demand shifters exhibit the expected signs: A larger residential population, more tourists and more in-commuters show significantly positive correlations with all measures of product variety, whereas the number of out-commuters is associated with less product variety. While the average household size is hardly related to restaurant variety, the coefficients on all age groups are positive relative to the reference category (comprising individuals younger than 15), but not all coefficients are significantly different from zero. Product variety is most strongly related to the share of individuals of the standard working age (the share of population aged 30-44 and 45-59), as expected. The number of H & M stores, indicating the presence of shopping areas in the municipality, is positively related to the number of restaurants (at the 10 % significance level) and to the index of horizontal variety, but not to the other two measures of product variety.

Table 5 summarizes the results for circular markets, where local markets are defined by drawing a circle with a radius of 5 kilometers around each individual restaurant (rather than relying on administrative boundaries). Measures of the inhabitants' educational attainments are used to proxy the local income distribution. The results are qualitatively very similar and reinforce the findings of the model using municipal data: The coefficients of the educational Gini index are significantly positive (at the 1 % significance level) for all measures of product variety. Inequality is therefore again associated with more restaurants, offering more diverse and less common cuisines. The average years of schooling are not only positively related to the number of restaurants and cuisines, but (unlike municipal markets) also with cuisine rarity.

We again illustrate the size of the coefficients on inequality in the regressions on the number of restaurants and the number of different cuisines, as depicted in Figure 5. While both panels show qualitatively similar results compared to municipal markets, two aspects are remarkable: First, using educational attainment as a proxy for income results in much lower

Table 5: Regression results on product variety based on circular markets

Dependent variable	Model [1] # restaurants	Model [2] # cuisines	Model [3] HV	Model [4] Rarity
Educational Gini index (in log)	2.034 ***	2.047 ***	0.067 ***	4.587 ***
	(0.075)	(0.051)	(0.004)	(0.240)
Mean years of education (in log)	6.296 ***	2.375 ***	−0.008	7.200 ***
	(0.137)	(0.064)	(0.007)	(0.472)
Ethnic diversity	1.125 ***	0.046 ***	0.036 ***	1.648 ***
	(0.020)	(0.008)	(0.001)	(0.069)
Population size (in log)	0.500 ***	0.317 ***	0.013 ***	1.032 ***
	(0.005)	(0.003)	(0.000)	(0.016)
Tourism (in log)	0.086 ***	0.038 ***	0.002 ***	0.150 ***
	(0.001)	(0.001)	(0.000)	(0.004)
In-commuters (in log)	0.043 ***	0.007 ***	0.005 ***	0.168 ***
	(0.005)	(0.002)	(0.000)	(0.018)
Out-commuters (in log)	−0.227 ***	−0.035 ***	−0.005 ***	−0.099 ***
	(0.006)	(0.003)	(0.000)	(0.021)
Average household size (in log)	−0.400 ***	−1.258 ***	−0.022 ***	0.480 **
	(0.068)	(0.047)	(0.004)	(0.240)
Share population aged 15-29	−5.447 ***	−5.152 ***	−0.205 ***	−1.893 *
	(0.274)	(0.151)	(0.015)	(1.012)
Share population aged 30-44	5.255 ***	−6.512 ***	−0.007	22.681 ***
	(0.392)	(0.233)	(0.021)	(1.403)
Share population aged 45-59	0.382	−4.028 ***	−0.043 ***	19.727 ***
	(0.301)	(0.204)	(0.016)	(1.099)
Share population aged 60-74	−0.735 **	−5.518 ***	−0.174 ***	7.233 ***
	(0.342)	(0.199)	(0.018)	(1.230)
Share population aged $\geq$ 75	−5.779 ***	−7.298 ***	−0.280 ***	−2.188 *
	(0.342)	(0.233)	(0.018)	(1.220)
# H & M stores (+1; in log)	0.453 ***	0.099 ***	0.032 ***	−0.017
	(0.009)	(0.004)	(0.000)	(0.032)
Constant	−11.844 ***	3.333 ***	0.260 ***	−23.950 ***
	(0.525)	(0.302)	(0.027)	(1.766)
Observations	24,421	24,421	24,421	24,421
Pseudo R^2	0.214	0.853		
R^2			0.919	0.839
Method	Negative binomial	Poisson	OLS	OLS

Notes: Circular markets are defined for each restaurant by drawing a radius of 5 km around the restaurant's location. Standard errors are reported in parentheses. *** significant at 1 %, ** significant at 5 %, * significant at 10 % level.

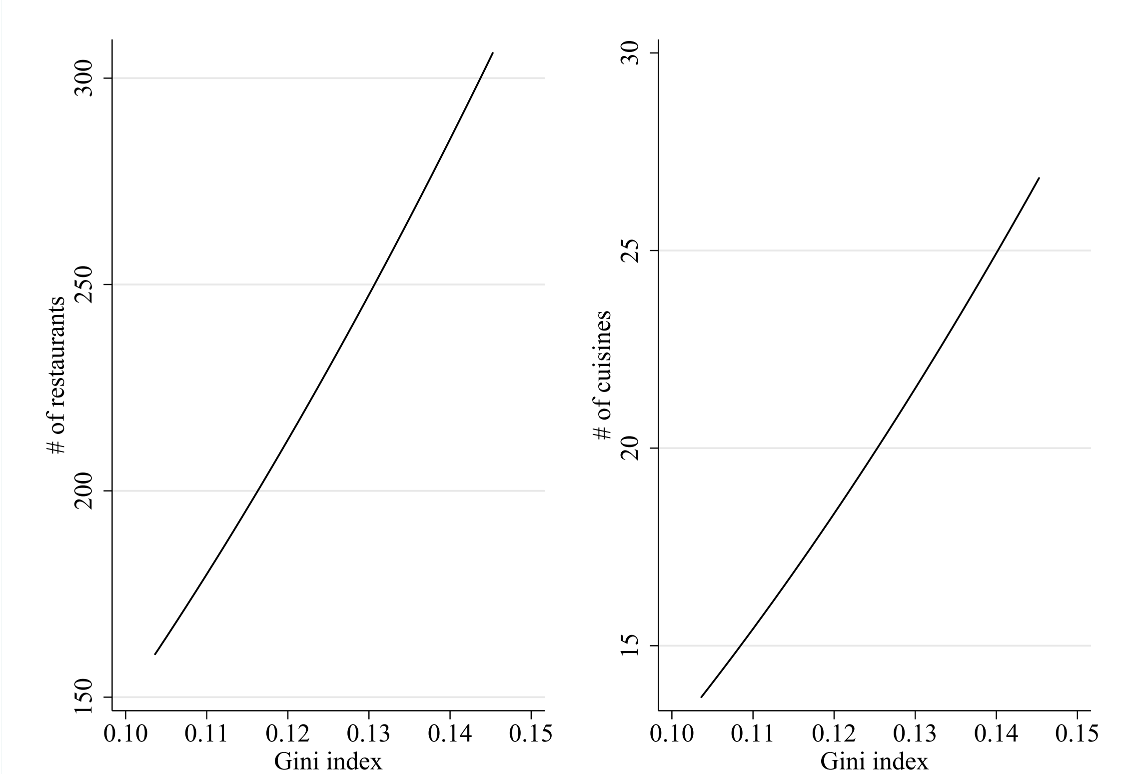
inequality, because the years of schooling are restricted between eight and 17 years. Second, the predicted numbers of restaurants and cuisines are much higher compared to municipal markets (see Figure 4). The reason for this difference is that a circular market is defined around each restaurant. An urban municipality with many restaurants thus results in many circular markets, whereas a rural municipality results in (at most) a small number of observations. Contrariwise, when using municipal markets, each municipality counts as exactly one observation (irrespective of the number of restaurants). Applying circular markets therefore results in local markets that are on average more urban, characterized by higher population densities and more restaurants. The size of the estimated coefficients on inequality, however, is higher compared to municipal markets—even in relative terms: The expected numbers of both restaurants and cuisines double (from 146 to 293 and from 13 to 26, respectively) when inequality increases from the 5^{th} to the 95^{th} percentile.

The results for most other variables indicating demand or demand heterogeneity are very similar to the findings based on municipal markets. The parameter estimates for ethnic diversity are significantly positive for all four measures of product differentiation. The area of the local markets is not included in the analysis, because all circular markets are of the same (geographic) size. Demand shifters as population size, tourism and in-commuters are positively, while out-commuters are negatively associated with all measures of product variety. The average household size (number of H & M stores) is negatively (positively) related to the number of restaurants, the number of cuisines and horizontal variety, while parameter estimates for the different age groups give less clear-cut results.

6 Sensitivity Analysis

In order to confirm that the results are not driven by the particular model specifications reported in the previous section, we perform a number of sensitivity analyses. We address the issue of reverse causality by splitting the sample along residential mobility in Section 6.1, use other measures of income inequality in Section 6.2, and apply alternative approaches to define markets and variables in Section 6.3.

Figure 5: Predicted number of restaurants and cuisines in circular markets



Notes: Figures illustrate the expected number of restaurants (left panel) and the expected number of different cuisines (right panel) in a circular local market, based on the parameter estimates reported in Model [1] and Model [2] of Table 5, respectively. Circular markets are defined for each restaurant by drawing a radius of 5 km around the restaurant's location. The Gini index varies from the 5^{th} to the 95^{th} percentile, while all other explanatory variables are set to their sample means.

6.1 Reverse Causality

As outlined in Section 3, our estimates may be affected by reverse causality, if markets with a high restaurant variety attract inhabitants in a way that systematically changes the income distribution in that local market. To address this issue, we split the sample based on gross migration rates and compare the respective regression results in markets with above-median mobility to markets characterized by below-median mobility. The results are summarized in Table 6, with Models [1] and [2] referring to municipal markets and Models [3] and [4] to circular markets.[27] Generally, we do not find evidence that the relationship between (income)

[27] All regressions include the same control variables as in the main specifications. The respective parameter estimates are not reported for brevity. The number of observations with low mobility is smaller in Panel (c) and Panel (d) for municipal markets, because the median mobility rate is calculated for the entire sample and markets without any restaurants (where horizontal variety and rarity cannot be calculated) are often markets with low residential mobility.

inequality and product variety is systematically related to residential mobility.

When analysing the number of restaurants (Panel (a)) or the number of cuisines (Panel (b)), the parameter estimates for the Gini index are significantly positive regardless of the market definition. When using the municipal delineation, the respective parameter estimates are somewhat larger for markets with higher residential mobility compared to low-mobility regions, but the differences are not significantly different from zero (see the respective χ^2 test statistics, reported in Table 6). For circular markets, on the other hand, the estimated coefficients are significantly larger in areas with less mobile residents. When investigating horizontal variety (Panel (c)) or cuisine rarity (Panel (d)), we find that the parameter estimates for inequality are larger in markets with above-median mobility when using municipal markets, but larger in below-median mobility areas when relying on circular markets. The differences are significantly different (at least at the 10 % level) for cuisine rarity, but not for horizontal variety. To sum up, we do not find systematically different parameter estimates for local markets characterized by either high or low residential mobility, suggesting that reverse causality is unlikely to be a major concern.

We also split the sample based on the minimum of immigration and emigration rates (instead of gross migration rates). Using the minimum values allows us to measure mobility without focusing on markets where this process is one-sided and the region is either rapidly expanding or shrinking (i.e. there are either high immigration or high emigration rates). The regression results based on this criterion to split the sample are very similar to the results reported in Table 6 and are thus relegated to Table A.5 in the appendix.

In addition, Table A.6 reports the results for a sample split along the median of the home ownership rates in 2011, rather than residential mobility. If we use this alternative sample split, we find that the parameter estimates on income inequality are larger in local markets with high home ownership rates (i.e. high mobility costs) in Panels (a), (b) and (d) at the aggregation level of municipal markets. The difference in the coefficients is statistically significant for Panels (a) and (b) at the 10 % significance level. At the circular market level, the parameter estimates are significantly smaller for high ownership rates in Panel (b), while the differences are not significantly different for all other measures of product variety. We again do not find that the effects are systematically different for markets with higher home ownership rates (i.e. high mobility costs and expected lower residential mobility) compared to markets with lower home ownership rates.

6.2 Alternative Measures of Inequality

To investigate the relationship between (income) inequality and product variety more thoroughly, we employ different measures of income inequality to see whether the results generated for the Gini index are corroborated. In particular, we employ the Theil and the Atkinson index, the 90/10, 90/50, 80/20 as well as the 50/10 quantile ratio. Table 7 (for municipal markets) and Table 8 (for circular markets) only report the parameter estimates on the variables indicating the income distribution, while results on all other control variables are suppressed for brevity. Using the Theil or the Atikinson index reveals virtually the same results as using the Gini index for both approaches to define local markets: The parameter estimates are positive for all measures of product variety and significantly different from zero at least at the 5 % significance level in 15 out of 16 regressions.

Results including quantile ratios are somewhat more nuanced: Considering the analysis based on municipal markets first (Table 7), we find a significantly positive parameter estimate for the 90/10 income quantile ratio for the number of restaurants and cuisines, but no significant coefficients for the other two measures of product variety. Using the 80/20 quantile ratio instead gives similar results, but statistical significance declines further. When including both the 90/50 and the 50/10 quantile ratio, we find significantly positive parameter estimates for the 90/50 ratio throughout, while the estimated coefficients of the 50/10 ratio are negative, but statistically different from zero in only one specification. The regression results for circular markets (Table 8) are similar: The parameter estimates of the 90/10 quantile ratio based on educational attainments are significantly positive for all measures of product variety. While the estimated coefficients are also positive for the 80/20 ratio, the size of the coefficients is smaller and the parameters are significantly different from zero at the 5 % level in two of the four models. Including both the 90/50 and the 50/10 ratio results in significantly positive parameter estimates for the first variable, but significantly negative coefficients for the latter one. The results on the 50/10 ratio, however, have to be interpreted cautiously, as we observe very little variation in this variable (if this ratio is based on

Table 6: Regression results on product variety: Sample split based on residential mobility

Sample split criterion:	Municipal markets		Circular markets	
Median of gross migration rate	at and below Model [1]	above Model [2]	at and below Model [3]	above Model [4]
Panel (a): negative binomial model of # of restaurants				
Gini index (in log)[a]	2.083 ***	3.185 ***	3.832 ***	1.495 ***
	(0.618)	(0.473)	(0.103)	(0.109)
Mean income (in log)[b]	1.397 ***	0.544 *	6.051 ***	7.053 ***
	(0.394)	(0.330)	(0.222)	(0.176)
Additional controls	yes	yes	yes	yes
Observations	1,178	1,182	12,245	12,176
Pseudo R^2	0.225	0.205	0.206	0.204
Equivalence test for the Gini index coefficient	[1] to [2]		[3] to [4]	
χ^2	1.84		71.50	
Prob > χ^2	0.175		0.000	
Panel (b): poisson model of # of cuisines				
Gini index (in log)[a]	1.137 ***	1.479 ***	3.117 ***	0.930 ***
	(0.395)	(0.354)	(0.083)	(0.072)
Mean income (in log)[b]	0.952 ***	0.499 **	2.050 ***	3.649 ***
	(0.263)	(0.253)	(0.116)	(0.096)
Additional controls	yes	yes	yes	yes
Observations	1,178	1,182	12,245	12,176
Pseudo R^2	0.594	0.454	0.866	0.721
Equivalence test for the Gini index coefficient	[1] to [2]		[3] to [4]	
χ^2	0.46		238.54	
Prob > χ^2	0.496		0.000	
Panel (c): OLS model of HV (horizontal variety)				
Gini index (in log)[a]	0.021	0.037 **	0.075 ***	0.062 ***
	(0.016)	(0.018)	(0.004)	(0.006)
Mean income (in log)[b]	0.019 *	−0.002	0.056 ***	−0.033 ***
	(0.011)	(0.013)	(0.011)	(0.010)
Additional controls	yes	yes	yes	yes
Observations	888	988	12,245	12,176
R^2	0.695	0.500	0.958	0.793
Equivalence test for the Gini index coefficient	[1] to [2]		[3] to [4]	
χ^2	0.35		0.49	
Prob > χ^2	0.554		0.484	
Panel (d): OLS model of R (rarity)				
Gini index (in log)[a]	−0.015	0.880 ***	7.366 ***	2.279 ***
	(0.347)	(0.303)	(0.348)	(0.354)
Mean income (in log)[b]	−0.137	0.187	4.292 ***	8.220 ***
	(0.223)	(0.213)	(0.866)	(0.609)
Additional controls	yes	yes	yes	yes
Observations	888	988	12,245	12,176
R^2	0.311	0.322	0.885	0.709
Equivalence test for the Gini index coefficient	[1] to [2]		[3] to [4]	
χ^2	3.53		9.67	
Prob > χ^2	0.060		0.002	

Notes: Circular markets are defined for each restaurant by drawing a radius of 5 km around the restaurant's location. Standard errors are reported in parentheses. *** significant at 1 %, ** significant at 5 %, * significant at 10 % level.
[a] For the regression on circular markets, the Educational Gini index (in log) is employed.
[b] For the regression on circular markets, the Mean years of education (in log) are employed

educational attainment rather than income).

The results based on the quantile ratios allow us to draw two conclusions. First, significance levels are much lower for quantile ratios compared to the Gini, Theil and Atkinson indices, suggesting that not only the range of the income distribution matters, but also the distribution within its upper and lower bounds. Second, the positive relationship between (income) inequality and product variety seems to be driven by inequality in the upper tail of the income distribution. This finding is in line with Falkinger (1994) and Falkinger and Zweimüller (1996, 1997). The argument is that if demand for variety depends on income, then wealthier consumers will demand a greater number of varieties than poorer consumers. Firms will only find it profitable to offer a new variety if the demand aggregation is large enough, i.e. if there are enough wealthy consumers willing to purchase this additional variety. With constant mean income, an increase in inequality will result in a larger number of varieties if the upper end of the income distribution grows sufficiently.

6.3 Market and Variable Definition and Sub-Sample Analysis

In order to investigate whether the results are robust to employing different radii around each individual restaurant when defining local markets, we report results for smaller radii (500 meters and 2 kilometers) as well as for a larger threshold distance of 10 kilometers (see Table A.7 in the appendix for the respective summary statistics). The parameter estimates on the educational Gini index, summarized in Table 9, are significantly positive at the 1 % significance level for all applied radii and for all four variables indicating product variety. While the results are very robust in this respect, the size of the coefficients tends to increase with larger threshold distances.

When using circular markets, local markets are defined by drawing a circle around each restaurant. If some restaurants are located very close to each other, these local markets cover similar areas and are nearly identical regarding restaurant variety and consumer heterogeneity. This might lead to an overestimation of the precision of the parameter estimates.[28] As

[28] This issue is similar, but not identical to the Moulton (1986) problem, when explanatory variables vary at a "group level" only. Ignoring within-group correlation leads to an underestimation of the standard errors of the respective parameter. As the local markets in our application overlap, typical solutions to the Moulton problem (like using clustered standard errors or group averages) cannot be applied.

Table 7: Regression results on product variety based on municipal markets using alternative measures of inequality

Dependent variable	Model [1] # restaurants	Model [2] # cuisines	Model [3] HV	Model [4] Rarity
Theil index (in log)	0.952 ***	0.480 ***	0.013 ***	0.194 **
	(0.151)	(0.103)	(0.005)	(0.089)
Mean income (in log)	0.901 ***	0.697 ***	0.004	0.041
	(0.252)	(0.174)	(0.008)	(0.151)
(Pseudo) R^2	0.214	0.526	0.586	0.320
Atkinson index (in log)	1.128 ***	0.550 ***	0.015 **	0.164
	(0.190)	(0.128)	(0.006)	(0.114)
Mean income (in log)	1.005 ***	0.766 ***	0.005	0.057
	(0.253)	(0.172)	(0.008)	(0.152)
(Pseudo) R^2	0.214	0.525	0.586	0.319
90/10 quantile ratio (in log)	0.431 ***	0.217 ***	0.005	−0.026
	(0.109)	(0.073)	(0.004)	(0.064)
Mean income (in log)	1.088 ***	0.865 ***	0.006	0.025
	(0.257)	(0.172)	(0.008)	(0.154)
(Pseudo) R^2	0.213	0.525	0.585	0.318
80/20 quantile ratio (in log)	0.395 **	0.201 *	0.004	−0.023
	(0.190)	(0.116)	(0.006)	(0.109)
Mean income (in log)	1.004 ***	0.849 ***	0.004	0.031
	(0.256)	(0.173)	(0.008)	(0.153)
(Pseudo) R^2	0.212	0.524	0.585	0.318
90/50 quantile ratio (in log)	1.971 ***	0.912 ***	0.028 ***	0.496 ***
	(0.311)	(0.236)	(0.008)	(0.178)
50/10 quantile ratio (in log)	−0.088	−0.080	−0.002	−0.189 **
	(0.146)	(0.120)	(0.004)	(0.082)
Mean income (in log)	1.093 ***	0.822 ***	0.006	0.125
	(0.256)	(0.175)	(0.007)	(0.150)
(Pseudo) R^2	0.215	0.529	0.501	0.353
Observations	2,360	2,360	1,876	1,876
Additional Controls	yes	yes	yes	yes
Method	Negative binomial	Poisson	OLS	OLS

Notes: Standard errors are reported in parentheses. *** significant at 1 %, ** significant at 5 %, * significant at 10 % level. Model [1] and Model [2] report the Pseudo R^2 statistic, while Model [3] and Model [4] report the standard R^2.

Table 8: Regression results on product variety based on circular markets using alternative measures of inequality

Dependent variable	Model [1] # restaurants	Model [2] # cuisines	Model [3] HV	Model [4] Rarity
Educational Theil index (in log)	1.221 ***	1.352 ***	0.038 ***	2.597 ***
	(0.050)	(0.033)	(0.002)	(0.154)
Mean years of education (in log)	6.538 ***	2.557 ***	0.001	7.849 ***
	(0.136)	(0.063)	(0.007)	(0.468)
Observations	24,421	24,421	24,421	24,421
(Pseudo) R^2	0.214	0.853	0.918	0.838
Educational Atkinson index (in log)	1.316 ***	1.434 ***	0.039 ***	2.595 ***
	(0.054)	(0.035)	(0.002)	(0.162)
Mean years of education (in log)	6.291 ***	2.227 ***	−0.004	7.491 ***
	(0.138)	(0.065)	(0.007)	(0.473)
Observations	24,421	24,421	24,421	24,421
(Pseudo) R^2	0.214	0.853	0.918	0.838
90/10 education quantile ratio (in log)	0.792 ***	0.556 ***	0.021 ***	2.213 ***
	(0.062)	(0.034)	(0.003)	(0.209)
Mean years of education (in log)	5.670 ***	2.415 ***	−0.027 ***	4.412 ***
	(0.174)	(0.076)	(0.009)	(0.604)
Observations	24,424	24,424	24,424	24,424
(Pseudo) R^2	0.213	0.851	0.917	0.837
80/20 education quantile ratio (in log)	0.557 ***	0.010	0.006 **	0.300 *
	(0.046)	(0.018)	(0.003)	(0.167)
Mean years of education (in log)	6.358 ***	3.123 ***	0.006	8.203 ***
	(0.145)	(0.075)	(0.007)	(0.500)
Observations	24,424	24,424	24,424	24,424
(Pseudo) R^2	0.212	0.851	0.917	0.836
90/50 education quantile ratio (in log)	0.599 ***	0.575 ***	0.015 ***	1.718 ***
	(0.061)	(0.034)	(0.003)	(0.209)
50/10 education quantile ratio (in log)	−5.121 ***	−3.232 ***	−0.124 ***	−10.243 ***
	(0.208)	(0.152)	(0.010)	(0.663)
Mean years of education (in log)	6.910 ***	2.640 ***	0.012	7.742 ***
	(0.175)	(0.076)	(0.009)	(0.622)
Observations	24,424	24,424	24,424	24,424
(Pseudo) R^2	0.215	0.852	0.918	0.839
Additional Controls	yes	yes	yes	yes
Method	Negative binomial	Poisson	OLS	OLS

Notes: Circular markets are defined for each restaurant by drawing a radius of 5 km around the restaurant's location. Standard errors are reported in parentheses. *** significant at 1 %, ** significant at 5 %, * significant at 10 % level. Model [1] and Model [2] report the Pseudo R^2 statistic, while Model [3] and Model [4] report the standard R^2.

Table 9: Regression results on product variety based on circular markets using alternative radii to define local markets

Method	Model [1] # restaurants Negative binomial	Model [2] # cuisines Poisson	Model [3] HV OLS	Model [4] Rarity OLS
Panel (a): 0.5 km radius				
Educational Gini index (in log)	1.239***	1.264***	0.034***	1.956***
	(0.059)	(0.038)	(0.003)	(0.213)
Mean years of education (in log)	6.828***	5.420***	0.206***	4.202***
	(0.106)	(0.053)	(0.006)	(0.491)
Additional controls	yes	yes	yes	yes
Observations	23,488	23,488	23,488	23,488
Pseudo R^2	0.200	0.704		
R^2			0.797	0.577
Panel (b): 2 km radius				
Educational Gini index (in log)	2.244***	1.823***	0.050***	3.726***
	(0.068)	(0.043)	(0.003)	(0.248)
Mean years of education (in log)	5.570***	3.414***	−0.019***	2.510***
	(0.109)	(0.048)	(0.006)	(0.478)
Additional controls	yes	yes	yes	yes
Observations	24,158	24,158	24,158	24,158
Pseudo R^2	0.229	0.846		
R^2			0.893	0.760
Panel (c): 10 km radius				
Educational Gini index (in log)	2.147***	2.135***	0.173***	6.496***
	(0.079)	(0.049)	(0.004)	(0.197)
Mean years of education (in log)	5.529***	2.781***	−0.015*	7.365***
	(0.159)	(0.073)	(0.008)	(0.387)
Additional controls	yes	yes	yes	yes
Observations	24,459	24,459	24,459	24,459
Pseudo R^2	0.193	0.833		
R^2			0.926	0.908

Notes: Standard errors are reported in parentheses. *** significant at 1 %, ** significant at 5 %, * significant at 10 % level. Additional control variables are calculated in the respective radius whenever possible.

a robustness exercise we thus restrict the exhaustive data set to a sub-sample of restaurants with hardly any local market overlap. We perform the selection of the sub-sample in a stepwise manner. We start by randomly selecting one restaurant, while discarding all other observations within the respective restaurant's 5 km threshold distance. From the remaining observations we again randomly pick one restaurant and discard the others located within a 5 km distance. We proceed this way until each restaurant of the sample is either selected or discarded, leaving a sub-sample of 1,224 restaurants (about 5 % of the entire data set). The regression results of this sub-sample are reported in Table 10. The parameter estimates on the Gini index remain significantly positive at the 1 % level for the number of restaurants, the number of different cuisines and cuisine rarity, and significantly positive at the 10 % level for horizontal variety, despite the substantial increase in standard errors due to the sharp reduction in sample size. Note that discarding 95 % of the sample reduces the variation in the data, because the discarded local markets are not exact duplicates of the markets included in this sub-sample. The estimated precision of the results reported in Table 10 is therefore very conservative.

Within the municipal market definition the issue of overlapping markets is resolved by construction. However, it is possible that market heterogeneity is correlated in space, thus undermining the independence assumption behind our main estimates. To address this concern, we implement a spatial error model (SEM), which explicitly accounts for the potential dependence of residuals across municipal borders (see, e.g., LeSage and Pace, 2009).[29] The results from this regression are reported in Table 11. The estimates of the effect of inequality on variety remain positive and significant. Furthermore, the magnitudes of the parameters and their standard errors are unaffected by the introduction of spatial correlation in the error term for Models [3] and [4]. A direct comparison of the results from the spatial model and our main specification is not possible for Models [1] and [2], as the introduction of spatial correlation in the errors required us to treat the dependent variable as continuous rather than discrete. However, there is clear evidence that inequality raises both the number of restaurants and the number of cuisines, with effects which are significant at the 1 % level.

[29] The distinction between the SEM model and our main specification lies in the modeling of the disturbance term, which we will denote by u. The error term of the variety function is estimated as $u = \rho W u + \varepsilon$, where W is a row-standardized spatial weights matrix based on contiguity and $\varepsilon \sim N(0, \sigma^2)$.

Table 10: Regression results on product variety based on circular markets for a sub sample

Dependent variable	Model [1] # restaurants	Model [2] # cuisines	Model [3] HV	Model [4] Rarity
Educational Gini index (in log)	1.338 ***	1.399 ***	0.022 *	3.742 ***
	(0.310)	(0.271)	(0.012)	(1.184)
Mean years of education (in log)	5.966 ***	2.356 ***	0.068 **	4.780
	(0.787)	(0.523)	(0.032)	(3.267)
Ethnic diversity	1.371 ***	0.553 ***	0.039 ***	1.887 ***
	(0.191)	(0.105)	(0.007)	(0.732)
Population size (in log)	0.470 ***	0.362 ***	0.009 ***	1.048 ***
	(0.022)	(0.019)	(0.001)	(0.082)
Tourism (in log)	0.082 ***	0.051 ***	0.002 ***	0.188 ***
	(0.005)	(0.004)	(0.000)	(0.023)
In-commuters (in log)	0.215 ***	0.211 ***	0.007 ***	0.583 ***
	(0.037)	(0.026)	(0.002)	(0.156)
Out-commuters (in log)	−0.380 ***	−0.243 ***	−0.005 **	−0.538 **
	(0.050)	(0.033)	(0.002)	(0.210)
Average household size (in log)	0.441	−0.074	0.016	3.336 **
	(0.335)	(0.264)	(0.014)	(1.370)
Share population aged 15-29	0.948	−2.391 *	−0.022	12.777
	(1.908)	(1.380)	(0.079)	(8.009)
Share population aged 30-44	12.423 ***	3.047 *	0.324 ***	63.070 ***
	(2.330)	(1.785)	(0.097)	(9.818)
Share population aged 45-59	8.733 ***	3.216 **	0.142 **	41.670 ***
	(1.563)	(1.297)	(0.067)	(6.754)
Share population aged 60-74	6.366 ***	2.280	0.047	33.010 ***
	(1.744)	(1.427)	(0.073)	(7.406)
Share population aged $\geq$ 75	−2.814	−5.262 ***	−0.022	9.010
	(1.768)	(1.315)	(0.072)	(7.285)
# H & M stores (+1; in log)	0.753 ***	0.194 ***	0.049 ***	1.153 ***
	(0.091)	(0.039)	(0.004)	(0.433)
Constant	−19.705 ***	−5.955 ***	−0.240 **	−44.770 ***
	(2.743)	(1.931)	(0.107)	(10.846)
Observations	1,224	1,224	1,224	1,224
Pseudo R^2	0.218	0.520		
R^2			0.561	0.422
Method	Negative binomial	Poisson	OLS	OLS

Notes: Circular markets are defined for each restaurant by drawing a radius of 5 km around the restaurant's location. The sub sample is selected such that each restaurant in this sample is not located within 5 km distance to any other restaurant also included in this sub sample. Standard errors are reported in parentheses. *** significant at 1 %, ** significant at 5 %, * significant at 10 % level.

Table 11: Regression results on product variety based on municipal markets (spatial error model specification)

Dependent variable	Model [1] # restaurants	Model [2] # cuisines	Model [3] HV	Model [4] Rarity
Gini index (in log)	89.799 ***	5.868 ***	0.030 **	0.427 *
	(14.145)	(1.060)	(0.013)	(0.232)
Mean income (in log)	9.632	−0.936	0.003	0.055
	(9.984)	(0.766)	(0.009)	(0.160)
Area (in log)	−0.688	−0.249 ***	−0.004 ***	−0.029 *
	(1.033)	(0.079)	(0.001)	(0.016)
Ethnic diversity	25.596 ***	4.561 ***	0.045 ***	0.342 ***
	(7.683)	(0.573)	(0.007)	(0.119)
Population size (in log)	50.975 ***	5.246 ***	0.063 ***	0.496 **
	(12.234)	(0.908)	(0.011)	(0.200)
Tourism (in log)	0.270	0.077 ***	0.001 ***	0.026 ***
	(0.187)	(0.014)	(0.000)	(0.003)
In-commuters (in log)	−1.925	−0.018	0.006 ***	0.125 ***
	(1.183)	(0.087)	(0.001)	(0.020)
Out-commuters (in log)	−40.186 ***	−3.638 ***	−0.051 ***	−0.437 **
	(11.910)	(0.883)	(0.011)	(0.195)
Average household size (in log)	−8.844	−3.215 ***	−0.015	−0.366 *
	(12.058)	(0.897)	(0.011)	(0.200)
Share population aged 15-29	389.801 ***	32.513 ***	0.274 ***	1.753
	(65.443)	(4.770)	(0.063)	(1.138)
Share population aged 30-44	438.238 ***	39.808 ***	0.448 ***	3.976 ***
	(78.785)	(5.809)	(0.075)	(1.361)
Share population aged 45-59	163.044 ***	15.113 ***	0.198 ***	2.668 ***
	(56.410)	(4.195)	(0.053)	(0.966)
Share population aged 60-74	239.359 ***	15.765 ***	0.166 ***	1.310
	(57.694)	(4.238)	(0.056)	(1.014)
Share population aged $\geq$ 75	291.608 ***	23.811 ***	0.195 ***	0.623
	(59.009)	(4.324)	(0.055)	(1.006)
# H & M stores (+1; in log)	159.005 ***	11.672 ***	0.048 ***	−0.032
	(5.659)	(0.408)	(0.005)	(0.088)
Constant	−387.819 ***	−22.227 **	−0.306 ***	−3.333 *
	(115.314)	(8.673)	(0.104)	(1.910)
Spatial correlation parameter ρ	0.416 ***	0.601 ***	0.145 ***	0.186 ***
	(0.022)	(0.018)	(0.031)	(0.030)
Observations	2,360	2,360	1,876	1,876
R^2	0.497	0.674	0.586	0.318
Method	SEM	SEM	SEM	SEM

Notes: Standard errors are reported in parentheses. *** significant at 1 %, ** significant at 5 %, * significant at 10 % level.

Austria's largest city, Vienna, hosts more than 21 % of the country's population and more than 28 % of all restaurants. To address concerns that the results might be driven exclusively by this market, Table A.8 (using municipal markets) and Table A.9 (applying circular markets) report regression results where the 23 districts of Vienna are excluded. The coefficients of the Gini index are positive for all model specifications and significantly different from zero in seven out of eight regressions. When restricting the analysis to restaurants located in Vienna only (Table A.10), the parameter estimates on the Gini index are positive for all models and significantly different from zero in all but one specification.[30] As the results remain very robust, the respective tables are reported in the appendix.

In the final sensitivity analysis, the restaurants classified as offering "unknown" cuisines are considered to offer Austrian cuisine, instead of assuming that the cuisines offered by these restaurants are distributed in the same way as the observed cuisines in a local market (as in the main specifications). The parameter estimates of the (educational) Gini index are significantly positive for all four measures of product variety for both municipal and circular markets. Table A.11 and Table A.12, summarizing the respective regression results, are thus relegated to the appendix. In further sensitivity analyses we include the measures of inequality (i.e. the respective indices and quantile ratios) in levels rather than in logs, and proxy the range of the income distribution by the differences between the respective income percentiles (rather than the ratios). As the qualitative results are hardly affected by these modifications, these results are reported in Table OA.1, Table OA.2 and Table OA.3 in an online-appendix only.

7 Conclusions and Extensions

Not only does inequality (in income and education) affect a number of socio-economic phenomena, like health, criminality, education or job growth, but it also influences the availability of locally produced and consumed goods and services. Theoretical models show that income inequality, among other factors, determines product variety; i.e. how many different products (horizontal variety) and which products (product hierarchy) are available. This has impor-

[30]When restricting the sample to restaurants located in Vienna, we only report results based on circular markets, as the municipal sample would comprise just 23 observations (namely the 23 districts of Vienna).

tant implications for consumer welfare. As noted by Glaeser et al. (2001), a large variety of services and consumer goods is one of the key urban amenities for cities to prosper. However, the relationship between local income dispersion and the available mix of consumer goods and services has received hardly any attention in the empirical literature so far.

The degree of income inequality differs between Western societies (Jaumotte et al., 2013), but also between individual regions within these societies. We investigate the relationship between income inequality and product variety for a specific non-tradeable consumer good: restaurant services. We collect a rich data set with information on the exact locations and the cuisines offered for individual restaurants in Austria and match this data set with information on residents' income levels and educational attainments at spatially fine scales. This allows us to calculate different measures of income inequality and to apply alternative concepts to define local markets.

The empirical analysis provides robust evidence for a positive relationship between income inequality and product variety: local markets with higher income inequality are characterized by a larger number of firms, offering a broader range of products, including less common product variants. The relationship between average income and product variety tends to be positive as well, but these results are less robust. While we remain tentative in pushing a causal interpretation of the results too far (because a rich variety of local goods might influence income inequality by attracting consumers of particular income segments), similar results for regions with high and low residential mobility suggest that the causality mainly runs from income inequality to product variety.

The findings provided in this article are consistent with both the characteristics approach and with hierarchic consumer preferences. If heterogeneity in consumers' preferences in Lancesterian (1966, 1979) models of product differentiation is reflected by the heterogeneity in consumers' income endowments, offering a large product variety is the market response to this heterogeneity. If consumers have hierarchic preferences (as in Falkinger and Zweimüller, 1996), larger income dispersion increases the number of consumers passing threshold income levels critical for demanding higher order products. In markets with a more unequal society, local demand for (higher order) niche products is larger, leading to a richer variety of products available. Our results are inconsistent with the assumption of homothetic consumer preferences, often used, for example, in models of monopolistic competition. With homothetic preferences, the variety of products available in a local market is independent of income distribution (income inequality), which is rejected in the present analysis.

Results when using different measures of inequality show that the statistical significance of the respective parameter estimates is highest for indices depending on the income levels of all individuals in a local market (i.e. Gini, Theil or Atkinson index) compared to measures indicating the range of the income distribution. This finding encourages theoretical approaches investigating firms' entry and product choices that model the entire income distribution (as done by Yurko, 2011)—despite the corresponding challenges regarding model tractability—relative to indicating income dispersion by simply changing the endpoints of the income distribution (as in Shaked and Sutton, 1982, 1983, 1987, Gabszewicz and Thisse, 1979, 1980).

The analysis in this paper focuses on a retail market that is likely to be representative for a number of other non-tradable consumption amenities. The findings suggest that markets which are diverse in terms of income endowments host more sellers and offer a wider choice of variety. However, welfare implications are not entirely straightforward. Welfare gains for consumers due to a larger variety may be compensated by higher prices, as more pronounced product differentiation leads to higher market power. Furthermore, these findings do not address issues related to distributional implications of welfare effects, since it is not possible for us to observe individual purchasing behavior. The additional welfare generated by the larger number of amenities may benefit consumers with a specific income more than others. Mazzolari and Neumark (2012) argue that low-income individuals gain less from an increase in variety compared to high-income individuals, since they might not be able to indulge in enjoying this increase in variety as much as a high-income individual can. In a theoretical model, Gulati and Ray (2016) suggest that firms choose to provide only products tailored for rich consumers at high prices, if income differences between rich and poor costumers become too large. This has adverse effects for poor consumers, who are excluded from consumption due to high prices. An extension of the present research to encompass such considerations would require information on purchase behavior in the entire food sector.

A further extension is possible by incorporating vertical differentiation into the analysis.

Product quality and product variety are interrelated in many ways. From the perspective of individual consumers, the interrelationship between vertical product differentiation (product quality) and the demand for variety is succinctly illustrated in Zeithammer and Thomadsen (2013): "... suppose you win a weekend of free dinners in Paris. If you care about quality, you surely wish to visit the top-rated restaurant in the city on one of your nights, but you would probably like to try another restaurant (by definition, lower quality) on the second night rather than go to the top-rated one again" (p. 390). Quality and variety are two substitutable dimensions in which firms can choose to differentiate. Our finding that the number of cuisines grows less than the total number of restaurants when income inequality rises is an indication that some of the differentiation may indeed be vertical. Since no objective quality measures were available for our data, we postpone further analysis of the interaction of these two effects to a later time.

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References

Aguiar, M. and Bils, M. (2015). Has consumption inequality mirrored income inequality? *American Economic Review*, 105(9):2725–56.

Allison, P. D. (1978). Measures of inequality. *American Sociological Review*, 43(6):865–880.

Atkinson, A. and Bourguignon, F. (2000). Income distribution and economics. In Atkinson, A. and Bourguignon, F., editors, *Handbook of Income Distribution*, pages 1–58. Elsevier.

Atkinson, A. B. (1970). On the measurement of inequality. *Journal of Economic Theory*, 2(3):244 – 263.

Behrman, J. and Deolalikar, A. (1989). Is variety the spice of life? Implications for calorie intake. *The Review of Economics and Statistics*, 71(4):666–672.

Berry, C. H. (1971). Corporate growth and diversification. *The Journal of Law and Economics*, 14(2):371–383.

Berry, S. and Waldfogel, J. (2010). Product quality and market size. *The Journal of Industrial Economics*, 58(1):1–31.

Broulíková, H. M., Huber, P., Montag, J., and Sunega, P. (2020). Homeownership, mobility, and unemployment: Evidence from housing privatization. *Journal of Housing Economics*, 50:101728.

Card, D. (1999). Chapter 30 - The Causal Effect of Education on Earnings. volume 3 of *Handbook of Labor Economics*, pages 1801 – 1863. Elsevier.

Chen, Y. and Rosenthal, S. S. (2008). Local amenities and life-cycle migration: Do people move for jobs or fun? *Journal of Urban Economics*, 64(3):519 – 537.

Christaller, W. (1933). *Central Places in Southern Germany.* Englewood Cliffs, NJ: Prentice Hall. (Translated by Carlisle W. Baskin).

Dalton, H. (1920). The measurement of the inequality of incomes. *Economic Journal*, 30:348 – 361.

Datta, S. and Sudhir, K. (2013). Does reducing spatial differentiation increase product differentiation? Effects of zoning on retail entry and format variety. *Quantitative Marketing and Economics*, 11(1):83–116.

Davis, D. R., Dingel, J. I., Monras, J., and Morales, E. (2019). How segregated is urban consumption? *Journal of Political Economy*, 127(4):1684–1738.

D'Hombres, B., Weber, A., and Elia, L. (2013). Literature review on income inequality and the effects on social outcomes. JRC Scientific and Policy Reports, Accessed: 2017-02-03.

Dixit, A. K. and Stiglitz, J. E. (1977). Monopolistic competition and optimum product diversity. *The American Economic Review*, 67(3):297–308.

Drakopoulos, S. (1994). Hierarchical choice in economics. *Journal of Economic Surveys*, 8(2):133–153.

Drescher, L., Thiele, S., and Weiss, C. R. (2008). The demand for variety: A hedonic analysis. *Economics Letters*, 101:66–68.

Falkinger, J. (1994). An Engelian model of growth and innovation with hierarchic consumer demand and unequal incomes. *Ricerche Economiche*, 48:123–139.

Falkinger, J. and Zweimüller, J. (1996). The cross-country Engel curve for product diversification. *Structural Change and Economic Dynamics*, 7(1):79–97.

Falkinger, J. and Zweimüller, J. (1997). The impact of income inequality on product diversity and economic growth. *Metronomica*, 48(3):211–237.

Foellmi, R. and Zweimüller, J. (2008). Structural change, Engel's consumption cycles and Kaldor's facts of economic growth. *Journal of Monetary Economics*, 55(7):1317 – 1328.

Foellmi, R. and Zweimüller, J. (2004). Inequality, market power, and product diversity. *Economics Letters*, 82:139–145.

Gabszewicz, J. J. and Thisse, J. F. (1979). Price competition, quality and income disparities. *Journal of Economic Theory*, 20:340–359.

Gabszewicz, J. J. and Thisse, J. F. (1980). Entry (and exit) in a differentiated industry. *Journal of Economic Theory*, 22(2):327–338.

George, L. and Waldfogel, J. (2003). Who affects whom in daily newspaper markets?. *Journal of Political Economy*, 111(4):765 – 784.

George, L. M. and Waldfogel, J. (2006). The New York Times and the market for local newspapers. *American Economic Review*, 96(1):435 – 447.

Glaeser, E. L. (2010). *Agglomeration Economics*. The University of Chcago Press, Chicago, IL.

Glaeser, E. L., Kolko, J., and Saiz, A. (2001). Consumer city. *Journal of Economic Geography*, 1(1):27–50.

Gulati, N. and Ray, T. (2016). Inequality, neighbourhoods and welfare of the poor. *Journal of Development Economics*, 122:214–228.

Hanushek, E. A. and Woessmann, L. (2008). The role of cognitive skills in economic development. *Journal of Economic Literature*, 46(3):607–68.

Henley, A. (1998). Residential mobility, housing equity and the labour market. *The Economic Journal*, 108(447):414–427.

Hsu, W.-T. (2012). Central place theory and city size distribution. *The Economic Journal*, 122(563):903–932.

Jackson, L. F. (1984). Hierarchic demand and the Engel curve for variety. *The Review of Economics and Statistics*, 66(1):8–15.

Jaffe, A. (1986). Technological opportunity and spillovers of R & D: Evidence from firms' patents, profits and market value. *The American Economic Review*, 76(5):984–1001.

Jaumotte, F., Lall, S., and Papageorgiou, C. (2013). Rising income inequality: Technology, or trade and financial globalization. *IMF Economic Review*, 61(2):271–309.

Koford, K. and Tschoegl, A. E. (1998). The market value of rarity. *Journal of Economic Behavior and Organization*, 34:445–457.

Krueger, A. B. and Lindahl, M. (2001). Education for growth: Why and for whom? *Journal of Economic Literature*, 39(4):1101–1136.

Lancaster, K. J. (1966). A new approach to consumer theory. *The Journal of Political Economy*, 74(2):132–157.

Lancaster, K. J. (1979). *Variety, Equity, and Efficiency.* New York: Columbia University Press.

LeSage, J. P. and Pace, R. K. (2009). *Introduction to Spatial Econometrics.* Boca Raton [et al.], CRC Press.

Long, J. S. and Freese, J. (2014). *Regression models for categorical dependent variables using Stata.* Stata Press, 3rd edition edition.

Lösch, A. (1944). *The Economics of Location.* New Haven, CT: Yale University Press. (Translated by W. Woglom).

Matsuyama, K. (1992). Agricultural productivity, comparative advantage, and economic growth. *Journal of Economic Theory*, 58(2):317 – 334.

Mazzolari, F. and Neumark, D. (2012). Immigration and product diversity. *Journal of Population Economics*, 25(3):1107–1137.

Mori, T., Nishikimi, K., and Smith, T. E. (2008). The number-average size rule: A new empirical relationship between industrial location and city size. *Journal of Regional Science*, 48(1):165–211.

Moser, M. and Schnetzer, M. (2017). The income–inequality nexus in a developed country: Small-scale regional evidence from Austria. *Regional Studies*, 51(3):454–466.

Moulton, B. (1986). Random group effects and the precision of regression estimates. *Journal of Econometrics*, 32(3):385–397.

Munch, J. R., Rosholm, M., and Svarer, M. (2006). Are homeowners really more unemployed?. *Economic Journal*, 116(514):991 – 1013.

Nishida, M. (2015). Estimating a model of strategic network choice: The convenience-store industry in Okinawa. *Marketing Science*, 34(1):20–38.

OECD (2008). *OECD Regions at a Glance 2007.* Paris.

OECD (2013). Technical report of the survey of adult skills (PIAAC). Paris.

Oswald, A. J. (1996). A conjecture on the explanation for high unemployment in the industrialized nations: Part 1. Working paper, Coventry.

Parenti, M., Ushchev, P., and Thisse, J.-F. (2017). Toward a theory of monopolistic competition. *Journal of Economic Theory*, 167:86 – 115.

Patil, G. P. and Taillie, C. (1982). Diversity as a concept and its measurement. *Journal of the American Statistical Association*, 77(379):548–561.

Pennerstorfer, A. and Pennerstorfer, D. (2019). How small are small markets? Local market size for child care services. *Regional Science and Urban Economics*, 77:340 – 355.

Persons, W. M. (1909). The variability in the distribution of wealth and income. *Quarterly Journal of Economics*, 23:416 – 449.

Schiff, N. (2015). Cities and product variety: Evidence from restaurants. *Journal of Economic Geography*, 15(6):1085–1123.

Schmidheiny, K. (2006). Income segregation and local progressive taxation: Empirical evidence from Switzerland. *Journal of Public Economics*, 90(3):429 – 458.

Schutz, R. R. (1951). On the measurement of income inequality. *American Economic Review*, 41:107 – 122.

Scott, A. J. (2010). Jobs or amenities? Destination choices of migrant engineers in the USA. *Papers in Regional Science*, 89(1):43–63.

Seim, K. (2006). An empirical model of firm entry with endogenous product-type choices. *RAND Journal of Economics*, 37(3):619–640.

Shaked, A. and Sutton, J. (1982). Relaxing price competition through product differentiation. *Review of Economic Studies*, 49(1):3–13.

Shaked, A. and Sutton, J. (1983). Natural oligopolies. *Econometrica*, 51(5):1469–1484.

Shaked, A. and Sutton, J. (1987). Product differentiation and industrial structure. *The Journal of Industrial Economics*, pages 131–146.

Shepard, A. (1991). Price discrimination and retail configuration. *Journal of Political Economy*, 99(1):30 – 53.

Shoag, D. and Veuger, S. (2019). Do land use restrictions increase restaurant quality and diversity? *Journal of Regional Science*, 59(3):435–451.

Stahl, K. (1983). A note on the microeconomics of migration. *Journal of Urban Economics*, 14(3):318 – 326.

Theil, H. and Finke, R. (1983). The consumer's demand for diversity. *European Economic Review*, 23(3):395–400.

Thiele, S. and Weiss, C. R. (2003). Consumer demand for food diversity: Evidence for Germany. *Food Policy*, 28:99–115.

Tiebout, C. M. (1956). A pure theory of local expenditures. *Journal of Political Economy*, 64:416 – 424.

Veblen, T. (1899). *The Theory of the Leisure Class: An Economic Study in the Evolution of Institutions*. Macmillan: New York.

Waldfogel, J. (2003). Preference externalities: An empirical study of who benefits whom in differentiated-product markets. *RAND Journal of Economics*, 34(3):557 – 568.

Waldfogel, J. (2008). The median voter and the median consumer: Local private goods and population composition. *Journal of Urban Economics*, 63(2):567 – 582.

Weiss, C. (2011). Consumer demand for food diversity. In Jayson, L., Roosen, J., and Shogren, J., editors, *Oxford Handbook on the Economics of Food Consumption and Policy*, pages 667–694. Oxford University Press.

Wolf, N. and Caruana-Galizia, P. (2015). Bombs, homes, and jobs: Revisiting the Oswald hypothesis for Germany. *Economics Letters*, 135:65 – 68.

Worchel, S., Lee, J., and Adewole, A. (1975). Effects of supply and demand on ratings of object value. *Journal of Applied Social Psychology*, 32:906 – 914.

Yurko, A. (2011). How does income inequality affect market outcomes in vertically differentiated markets? *International Journal of Industrial Organization*, 29(4):493–503.

Zeithammer, R. and Thomadsen, R. (2013). Vertical differentiation with variety-seeking consumers. *Management Science*, 59(2):390–401.

Zhu, T. and Singh, V. (2009). Spatial competition with endogenous location choices: An application to discount retailing. *Quantitative Marketing and Economics*, 7:1–35.

Zweimüller, J. (2000). Schumpeterian entrepreneurs meet Engel's law: The impact of inequality on innovation-driven growth. *Journal of Economic Growth*, 5:185–206.

Appendix

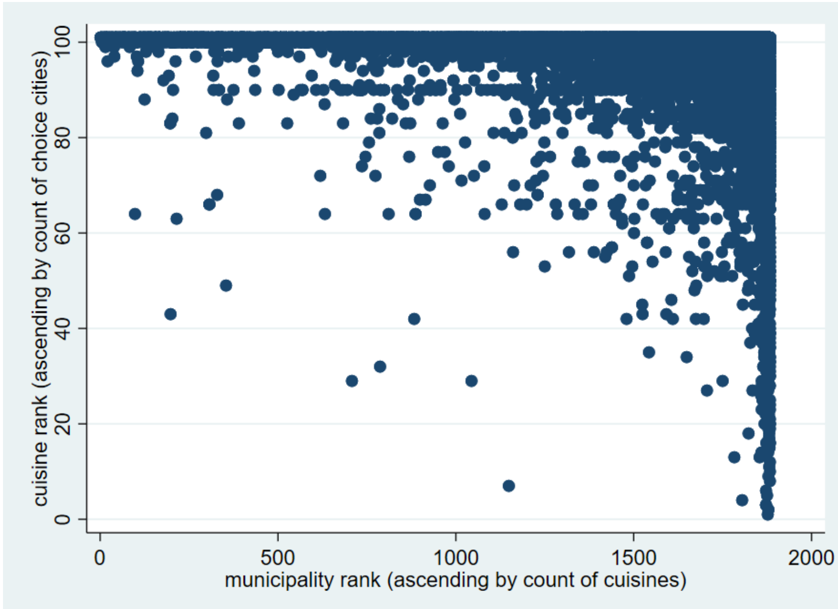
Table A.1: Correlation between educational Gini indices using circular markets with different radii (N = 23,505)

Threshold radius	0.5 km	2 km	5 km	10 km
0.5 km	1			
2 km	0.784	1		
5 km	0.696	0.918	1	
10 km	0.636	0.847	0.943	1

Table A.2: The rarest rarest and most common cuisines

N	Rarest Cuisines	Municipality	N	Most Common Cuisines	Choice Cities
1	Cuban	Linz	8,287	Austrian	1,805
1	Indonesian	Vienna 1st district	1,593	Italian	377
1	Tunisian	Vienna 1st district	999	International	352
1	Kurdish	Vienna 1st district	577	Pizza	268
1	Nepalese	Hall/ Tyrol	577	German	197
1	Kosher	Vienna 2nd district	576	Snacks	184
1	Portuguese	Vienna 5th district	522	Chinese	165
1	Israeli	Vienna 2nd district	353	European	149
1	Pakistani	Vienna 9th district	377	American	135
1	Ukrainian	Vienna 3rd district	358	Café	127

Figure A.1: Hierarchy Diagram



In Figure A.1 we show a hierarchy diagram similar to the ones depicted in Mori et al. (2008) and Schiff (2015). For the horizontal axis, the municipalities were ranked by the number of cuisines which are available in that municipality. The highest rank is assigned to the municipality featuring the highest number of different cuisines. For our case this is Vienna's first district which offers 73 different cuisines out of the 101 cuisines that are available in Austria. Accordingly, for the vertical axis the cuisines are ranked depending on the number of municipalities in which they are available (Schiff (2015) called these 'choice cities'). For cuisines, rank 1 is assigned to a cuisine which is only available in one municipality and can therefore be interpreted as a measure of rarity. The higher the cuisine rank, the more common the cuisine. The observations plotted in A.1 consist of municipality-cuisine pairs. It shows that, in line with Schiff (2015), who observes a hierarchical pattern for cuisines in American cities, we also observe a hierarchical pattern for cuisines in Austria. Rarer cuisines are generally offered in municipalities with more cuisines. If there are fewer cuisines offered in a municipality, these are generally more common cuisines. As outlined in Schiff (2015), one could make predictions about which cuisines are available in a given municipality by simply knowing the count of cuisines available in this market.

Table A.3: Summary statistics on municipal markets

	Variables	N	mean	S. D.	min	max
Variety	# of restaurants	2,379	10.190	47.689	0	1,170
	# of cuisines	2,379	2.305	4.694	0	72
	HV	1,883	0.127	0.042	0.100	0.397
	Rarity (scaled by 1/1,000)	1,883	0.570	0.595	0	1.739
Heterogeneity	Gini index	2,360	0.400	0.024	0.320	0.550
	Educational Gini index	2,379	0.099	0.009	0.066	0.140
	Theil index	2,360	0.283	0.046	0.171	0.915
	Atkinson index	2,360	0.145	0.018	0.092	0.297
	90/10 percentile	2,360	9.938	2.632	4.459	58.658
	80/20 percentile	2,360	3.767	0.611	2.801	17.474
	90/50 percentile	2,360	2.233	0.168	1.681	3.431
	50/10 percentile	2,360	4.424	0.908	2.241	19.264
	Area (in km^2)	2,379	45.292	49.396	0.113	466.799
	Ethnic diversity	2,379	1.138	0.140	1	2.969
Demand Shifters	Mean income (in thousand €)	2,360	26.708	3.312	18.059	49.069
	Mean years of schooling	2,379	11.160	0.358	9.648	13.270
	Population size (in thousands)	2,379	4.155	12.431	0.046	274.207
	Tourism (in thousands)	2,379	56.185	183.270	0.001	2,720.922
	In-commuters (in thousands)	2,379	1.534	7.679	0.005	169.654
	Out-commuters (in thousands)	2,379	1.534	5.241	0.02	117.647
	Average household size	2,379	2.570	0.290	1.769	3.896
	Share population aged 15-29	2,379	0.178	0.022	0.091	0.287
	Share population aged 30-44	2,379	0.202	0.020	0.093	0.278
	Share population aged 45-59	2,379	0.234	0.020	0.111	0.430
	Share population aged 60-74	2,379	0.154	0.025	0.058	0.273
	Share population aged $\geq$ 75	2,379	0.086	0.02	0.035	0.307
	# H & M stores	2,379	0.034	0.238	0	5
	Gross migration rate	2,379	0.084	0.035	0.011	0.651
	Min of im- and emigration rate	2,379	0.037	0.016	0	0.242

Table A.4: Summary statistics on circular markets

	Variables	N	mean	S. D.	min	max
Variety	# of restaurants[a]	24,460	1,392	2,161	1	5,726
	# of cuisines[a]	24,460	35.484	35.554	1	95
	HV[a]	24,460	0.234	0.088	0.100	0.362
	Rarity[a] (scaled by 1/1,000)	24,460	9.984	4.175	0	23.963
Heterogeneity	Educational Gini index[b]	24,424	0.125	0.015	0	0.194
	Educational Theil index[b]	24,424	0.027	0.005	0	0.040
	Educational Atkinson index[b]	24,424	0.027	0.005	0	0.040
	90/10 Education Ratio[b]	24,424	1.915	0.232	1	2.125
	80/20 Education Ratio[b]	24,424	1.679	0.236	1	2.125
	90/50 Education Ratio[b]	24,424	1.281	0.150	1	1.625
	50/10 Education Ratio[b]	24,424	1.494	0.028	1	1.625
	Ethnic diversity[c]	24,460	1.403	0.284	1.003	2.969
Demand Shifters	Mean years of schooling[b]	24,424	11.549	0.448	8	14.500
	Population size[b] (in thousands)	24,460	211.115	309.711	0	896.476
	Tourism[c] (in thousands)	24,460	588.151	740.189	0.001	2,720.923
	In-commuters[c] (in thousands)	24,460	33.165	47.346	0.007	169.654
	Out-commuters[c] (in thousands)	24,460	19.933	29.330	0.035	117.647
	Average household size[c]	24,460	2.189	0.273	1.820	3.910
	Share population aged 15-29[c]	24,460	0.187	0.028	0.106	0.287
	Share population aged 30-44[c]	24,460	0.211	0.021	0.093	0.278
	Share population aged 45-59[c]	24,460	0.223	0.018	0.140	0.430
	Share population aged 60-74[c]	24,460	0.160	0.025	0.058	0.272
	Share population aged $\geq$ 75[c]	24,460	0.082	0.019	0.035	0.307
	# H & M stores[a]	24,460	3.194	4.243	0	13
	Gross migration rate	24,455	0.075	0.033	0.021	0.651
	Min of im- and emigration rate	24,460	0.034	0.015	0.006	0.242

Notes: Threshold radius to define local markets equal to 5 km.
[a] Variables are based on the exact locations of restaurants and H & M stores, respectively.
[b] Variables are based on the spatial distribution of the population at the 250 m × 250 m grid cell level.
[c] Variables are based on the municipality, where the restaurant is located.

Table A.5: Regression results on product variety: Sample split based on alternative measure of residential mobility

Sample split criterion:	Municipal Markets		Circular Markets	
Median of min(immigration rate, emigration rate)	at and below Model [1]	above Model [2]	at and below Model [3]	above Model [4]
Panel (a): negative binomial model of # of restaurants				
Gini index (in log)[a]	2.170 ***	3.074 ***	3.502 ***	1.647 ***
	(0.631)	(0.467)	(0.102)	(0.108)
Mean income (in log)[b]	1.340 ***	0.547 *	6.588 ***	6.748 ***
	(0.390)	(0.330)	(0.218)	(0.175)
Additional controls	yes	yes	yes	yes
Observations	1,174	1,186	12,279	12,142
Pseudo R^2	0.225	0.206	0.206	0.205
Equivalence test for the Gini index coefficient	[1] to [2]		[3] to [4]	
χ^2	1.24		46.19	
Prob > χ^2	0.265		0.000	
Panel (b): poisson model of # of cuisines				
Gini index (in log)[a]	1.365 ***	1.359 ***	3.202 ***	1.069 ***
	(0.391)	(0.358)	(0.085)	(0.070)
Mean income (in log)[b]	1.029 ***	0.436 *	2.159 ***	3.628 ***
	(0.254)	(0.255)	(0.115)	(0.097)
Additional controls	yes	yes	yes	yes
Observations	1,174	1,186	12,279	12,142
Pseudo R^2	0.594	0.456	0.868	0.716
Equivalence test for the Gini index coefficient	[1] to [2]		[3] to [4]	
χ^2	0.00		231.87	
Prob > χ^2	0.991		0.000	
Panel (c): OLS model of HV (horizontal variety)				
Gini index (in log)[a]	0.026	0.037 **	0.076 ***	0.061 ***
	(0.016)	(0.018)	(0.004)	(0.006)
Mean income (in log)[b]	0.018 *	−0.005	0.067 ***	−0.033 ***
	(0.010)	(0.013)	(0.011)	(0.010)
Additional controls	yes	yes	yes	yes
Observations	878	998	12,279	12,142
R^2	0.691	0.508	0.958	0.794
Equivalence test for the Gini index coefficient	[1] to [2]		[3] to [4]	
χ^2	0.17		0.62	
Prob > χ^2	0.676		0.430	
Panel (d): OLS model of R (rarity)				
Gini index (in log)[a]	0.212	0.730 **	7.036 ***	2.600 ***
	(0.349)	(0.302)	(0.348)	(0.354)
Mean income (in log)[b]	−0.109	0.200	6.263 ***	7.839 ***
	(0.219)	(0.213)	(0.842)	(0.612)
Additional controls	yes	yes	yes	yes
Observations	878	998	12,279	12,142
R^2	0.302	0.335	0.883	0.711
Equivalence test for the Gini index coefficient	[1] to [2]		[3] to [4]	
χ^2	1.21		7.86	
Prob > χ^2	0.272		0.005	

Notes: Circular markets are defined for each restaurant by drawing a radius of 5 km around the restaurant's location. Standard errors are reported in parentheses. *** significant at 1 %, ** significant at 5 %, * significant at 10 % level.

[a] For the regression on circular markets, the Educational Gini index (in log) is employed.

[b] For the regression on circular markets, the Mean years of education (in log) are employed

Table A.6: Regression results on product variety: Sample split based on home ownership rate

Sample split criterion:	Municipal markets		Circular markets	
Median of home ownership rate	at and below Model [1]	above Model [2]	at and below Model [3]	above Model [4]
Panel (a): negative binomial model of # of restaurants				
Gini index (in log)[a]	2.141 ***	3.694 ***	1.795 ***	1.695 ***
	(0.413)	(0.770)	(0.094)	(0.101)
Mean income (in log)[b]	0.641 **	1.267 **	5.046 ***	5.031 ***
	(0.298)	(0.502)	(0.113)	(0.227)
Additional controls	yes	yes	yes	yes
Observations	1,186	1,174	11,901	12,520
Pseudo R^2	0.217	0.099	0.213	0.140
Equivalence test for the Gini index coefficient	[1] to [2]		[3] to [4]	
χ^2	3.01		0.14	
Prob > χ^2	0.083		0.709	
Panel (b): poisson model of # of cuisines				
Gini index (in log)[a]	0.959 ***	2.014 ***	2.239 ***	1.706 ***
	(0.278)	(0.651)	(0.090)	(0.065)
Mean income (in log)[b]	0.591 ***	0.539	2.107 ***	1.751 ***
	(0.202)	(0.429)	(0.087)	(0.130)
Additional controls	yes	yes	yes	yes
Observations	1,186	1,174	11,901	12,520
Pseudo R^2	0.564	0.110	0.729	0.444
Equivalence test for the Gini index coefficient	[1] to [2]		[3] to [4]	
χ^2	3.01		16.09	
Prob > χ^2	0.083		0.000	
Panel (c): OLS model of HV (horizontal variety)				
Gini index (in log)[a]	0.033 *	0.022	0.068 ***	0.046 ***
	(0.018)	(0.014)	(0.007)	(0.005)
Mean income (in log)[b]	0.011	0.004	−0.025 ***	−0.011
	(0.012)	(0.010)	(0.009)	(0.011)
Additional controls	yes	yes	yes	yes
Observations	1,077	799	11,901	12,520
R^2	0.607	0.171	0.921	0.554
Equivalence test for the Gini index coefficient	[1] to [2]		[3] to [4]	
χ^2	0.21		2.37	
Prob > χ^2	0.646		0.123	
Panel (d): OLS model of R (rarity)				
Gini index (in log)[a]	0.072	0.800 **	3.489 ***	4.096 ***
	(0.278)	(0.384)	(0.214)	(0.342)
Mean income (in log)[b]	0.422 **	−0.396	5.036 ***	3.043 ***
	(0.191)	(0.264)	(0.279)	(0.810)
Additional controls	yes	yes	yes	yes
Observations	1,077	799	11,901	12,520
R^2	0.354	0.098	0.950	0.487
Equivalence test for the Gini index coefficient	[1] to [2]		[3] to [4]	
χ^2	2.41		0.43	
Prob > χ^2	0.120		0.512	

Notes: Circular markets are defined for each restaurant by drawing a radius of 5 km around the restaurant's location. Standard errors are reported in parentheses. *** significant at 1 %, ** significant at 5 %, * significant at 10 % level.
[a] For the regression on circular markets, the Educational Gini index (in log) is employed.
[b] For the regression on circular markets, the Mean years of education (in log) are employed

Table A.7: Summary statistics on circular markets of different market size

	Variables	N	mean	S. D.	min	max
Variety	# of restaurants (0.5 km)	24,460	60.985	108.121	1	568
	# of restaurants (2 km)	24,460	497.635	897.205	1	3,250
	# of restaurants (5 km)	24,460	1,392.245	2,161.466	1	5,726
	# of restaurants (10 km)	24,460	2,109.712	2,906.299	1	6,978
	# of cuisines (0.5 km)	24,460	11.371	13.789	1	58
	# of cuisines (2 km)	24,460	25.416	29.475	1	91
	# of cuisines (5 km)	24,460	35.484	35.554	1	95
	# of cuisines (10 km)	24,460	42.374	36.236	1	96
	HV (0.5 km)	24,460	0.203	0.097	0.100	0.419
	HV (2 km)	24,460	0.226	0.095	0.100	0.384
	HV (5 km)	24,460	0.234	0.088	0.100	0.362
	HV (10 km)	24,460	0.233	0.081	0.100	0.355
	Rarity (0.5 km; scaled by 1/1,000)	24,460	8.892	5.761	0	21.008
	Rarity (2 km; scaled by 1/1,000)	24,460	9.964	5.149	0	23.492
	Rarity (5 km; scaled by 1/1,000)	24,460	9.984	4.175	0	23.963
	Rarity (10 km; scaled by 1/1,000)	24,460	9.180	3.553	0	13.675
Heterogen.	Educational Gini index (0.5 km)	23,505	0.123	0.016	0	0.360
	Educational Gini index (2 km)	24,168	0.124	0.015	0	0.194
	Educational Gini index (5 km)	24,424	0.125	0.015	0	0.194
	Educational Gini index (10 km)	24,459	0.124	0.013	0.061	0.147
Demand Shifters	Mean years of schooling (0.5 km)	23,509	11.809	0.882	8	14.750
	Mean years of schooling (2 km)	24,168	11.674	0.648	8	13.818
	Mean years of schooling (5 km)	24,424	11.549	0.448	8	14.500
	Mean years of schooling (10 km)	24,459	11.512	0.387	9.667	12.893
	Population size (0.5 km; in thousands)	24,460	4.258	5.700	0	30.297
	Population size (2 km; in thousands)	24,460	52.104	71.494	0	254.012
	Population size (5 km; in thousands)	24,460	211.115	309.711	0	896.476
	Population size (10 km; in thousands)	24,460	258.337	339.597	0.002	1,169.234
	# H & M stores (0.5 km)	24,460	0.204	0.508	0	3
	# H & M stores (2 km)	24,460	1.115	1.790	0	7
	# H & M stores (5 km)	24,460	3.194	4.243	0	13
	# H & M stores (10 km)	24,460	5.526	6.872	0	19
	Gross migration rate	24,455	0.075	0.033	0.021	0.651
	Min of im- and emigration rate	24,460	0.034	0.015	0.006	0.242

Notes: Threshold radius to define local markets in brackets. Summary statistics of variables available at the municipal level only are not reported.

Table A.8: Regression results on product variety based on municipal markets excluding Vienna

Dependent variable	Model [1] # restaurants	Model [2] # cuisines	Model [3] HV	Model [4] Rarity
Gini index (in log)	2.329 ***	1.012 ***	0.008	0.546 **
	(0.395)	(0.299)	(0.012)	(0.232)
Mean income (in log)	0.947 ***	0.751 ***	0.005	0.034
	(0.259)	(0.188)	(0.008)	(0.154)
Area (in log)	0.109 ***	−0.003	−0.003 ***	−0.040 **
	(0.026)	(0.020)	(0.001)	(0.016)
Ethnic diversity	1.371 ***	0.678 ***	0.037 ***	0.449 ***
	(0.222)	(0.119)	(0.007)	(0.122)
Population size (in log)	2.466 ***	2.048 ***	0.059 ***	0.532 ***
	(0.310)	(0.227)	(0.010)	(0.196)
Tourism (in log)	0.110 ***	0.071 ***	0.001 ***	0.028 ***
	(0.005)	(0.005)	(0.000)	(0.003)
In-commuters (in log)	0.347 ***	0.290 ***	0.008 ***	0.114 ***
	(0.037)	(0.029)	(0.001)	(0.021)
Out-commuters (in log)	−2.243 ***	−1.865 ***	−0.051 ***	−0.450 **
	(0.298)	(0.217)	(0.010)	(0.191)
Average household size (in log)	−0.335	−0.516 *	−0.005	−0.256
	(0.341)	(0.281)	(0.011)	(0.196)
Share population aged 15-29	2.054	2.656 *	0.137 **	2.726 **
	(2.072)	(1.538)	(0.063)	(1.183)
Share population aged 30-44	10.873 ***	8.315 ***	0.315 ***	5.921 ***
	(2.397)	(1.866)	(0.074)	(1.384)
Share population aged 45-59	7.472 ***	5.318 ***	0.159 ***	3.687 ***
	(1.607)	(1.349)	(0.051)	(0.954)
Share population aged 60-74	5.443 ***	3.117 **	0.114 **	2.335 **
	(1.765)	(1.466)	(0.054)	(1.018)
Share population aged $\geq$ 75	1.219	0.515	0.078	1.588
	(1.817)	(1.468)	(0.055)	(1.032)
# H & M stores (in 1 + log)	0.250 *	0.026	0.050 ***	−0.013
	(0.149)	(0.063)	(0.005)	(0.097)
Constant	−19.211 ***	−15.459 ***	−0.259 ***	−4.381 **
	(3.126)	(2.348)	(0.100)	(1.864)
Observations	2,337	2,337	1,853	1,853
Pseudo R^2	0.189	0.403		
R^2			0.479	0.298
Method	Negative binomial	Poisson	OLS	OLS

Notes: Standard errors are reported in parentheses. *** significant at 1 %, ** significant at 5 %, * significant at 10 % level.

Table A.9: Regression results on product variety based on circular markets excluding Vienna

Dependent variable	Model [1] # restaurants	Model [2] # cuisines	Model [3] HV	Model [4] Rarity
Educational Gini index (in log)	2.053 ***	1.462 ***	0.063 ***	4.449 ***
	(0.085)	(0.057)	(0.004)	(0.280)
Mean years of education (in log)	6.804 ***	3.288 ***	−0.001	5.866 ***
	(0.165)	(0.091)	(0.009)	(0.589)
Ethnic diversity	1.021 ***	0.576 ***	0.039 ***	1.630 ***
	(0.034)	(0.018)	(0.002)	(0.113)
Population size (in log)	0.504 ***	0.376 ***	0.013 ***	1.193 ***
	(0.006)	(0.005)	(0.000)	(0.021)
Tourism (in log)	0.084 ***	0.040 ***	0.002 ***	0.160 ***
	(0.001)	(0.001)	(0.000)	(0.005)
In-commuters (in log)	0.224 ***	0.182 ***	0.010 ***	0.505 ***
	(0.009)	(0.006)	(0.000)	(0.032)
Out-commuters (in log)	−0.452 ***	−0.246 ***	−0.012 ***	−0.692 ***
	(0.011)	(0.007)	(0.001)	(0.040)
Average household size (in log)	−0.097	−0.434 ***	−0.018 ***	0.976 ***
	(0.083)	(0.055)	(0.004)	(0.299)
Share population aged 15-29	1.605 ***	−0.363	0.009	12.422 ***
	(0.393)	(0.240)	(0.021)	(1.444)
Share population aged 30-44	13.725 ***	−0.103	0.224 ***	46.519 ***
	(0.540)	(0.372)	(0.029)	(1.961)
Share population aged 45-59	5.530 ***	3.020 ***	0.124 ***	35.009 ***
	(0.366)	(0.277)	(0.020)	(1.375)
Share population aged 60-74	6.367 ***	−0.889 ***	−0.004	22.535 ***
	(0.440)	(0.291)	(0.023)	(1.592)
Share population aged $\geq$ 75	−2.829 ***	−4.983 ***	−0.201 ***	6.542 ***
	(0.425)	(0.304)	(0.022)	(1.523)
# H & M stores (+1; in log)	0.338 ***	0.030 ***	0.033 ***	0.135 ***
	(0.013)	(0.006)	(0.001)	(0.047)
Constant	−18.369 ***	−6.489 ***	0.088 ***	−35.150 ***
	(0.609)	(0.360)	(0.031)	(2.118)
Observations	17,405	17,405	17,405	17,405
Pseudo R^2	0.186	0.686		
R^2			0.788	0.676
Method	Negative binomial	Poisson	OLS	OLS

Notes: Circular markets are defined for each restaurant by drawing a radius of 5 km around the restaurant's location. Standard errors are reported in parentheses. *** significant at 1 %, ** significant at 5 %, * significant at 10 % level.

Table A.10: Regression results on product variety based on circular markets including only Vienna

Dependent variable	Model [1] # restaurants	Model [2] # cuisines	Model [3] HV	Model [4] Rarity
Educational Gini index (in log)	3.995 ***	4.213 ***	0.011	14.809 ***
	(0.113)	(0.176)	(0.010)	(0.287)
Mean years of education (in log)	5.647 ***	1.369 ***	0.147 ***	0.618 **
	(0.107)	(0.152)	(0.010)	(0.280)
Ethnic diversity	0.057 ***	−0.109 ***	−0.019 ***	−0.315 ***
	(0.009)	(0.012)	(0.001)	(0.024)
Population size (in log)	0.860 ***	0.296 ***	0.044 ***	0.909 ***
	(0.009)	(0.014)	(0.001)	(0.022)
Tourism (in log)	−0.027 ***	−0.015 ***	0.006 ***	−0.022 ***
	(0.002)	(0.003)	(0.000)	(0.006)
In-commuters (in log)	0.056 ***	0.034 ***	−0.002 ***	0.109 ***
	(0.004)	(0.005)	(0.000)	(0.010)
Out-commuters (in log)	0.039 ***	−0.001	−0.001	−0.096 ***
	(0.006)	(0.008)	(0.001)	(0.016)
Average household size (in log)	1.028 ***	1.065 ***	−0.093 ***	1.713 ***
	(0.158)	(0.210)	(0.015)	(0.441)
Share population aged 15-29	−0.592	−0.520	−0.678 ***	−4.810 ***
	(0.388)	(0.516)	(0.037)	(1.082)
Share population aged 30-44	5.206 ***	0.484	−0.636 ***	−8.505 ***
	(0.574)	(0.771)	(0.055)	(1.599)
Share population aged 45-59	−4.596 ***	−2.151 ***	−1.078 ***	−7.362 ***
	(0.535)	(0.722)	(0.051)	(1.470)
Share population aged 60-74	3.983 ***	−0.757	−0.413 ***	−13.973 ***
	(0.472)	(0.640)	(0.045)	(1.311)
Share population aged $\geq$ 75	−0.259	0.075	−0.906 ***	−1.149
	(0.636)	(0.851)	(0.061)	(1.773)
# H & M stores (+1; in log)	0.479 ***	0.120 ***	0.015 ***	0.429 ***
	(0.006)	(0.009)	(0.001)	(0.015)
Constant	−12.809 ***	4.855 ***	0.047	35.089 ***
	(0.720)	(1.033)	(0.066)	(1.919)
Observations	7,016	7,016	7,016	7,016
Pseudo R^2	0.220	0.441		
R^2			0.928	0.958
Method	Negative binomial	Poisson	OLS	OLS

Notes: Circular markets are defined for each restaurant by drawing a radius of 5 km around the restaurant's location. Standard errors are reported in parentheses. *** significant at 1 %, ** significant at 5 %, * significant at 10 % level.

Table A.11: Regression results on product variety based on municipal markets with "unknown" cuisines considered as Austrian cuisine

Dependent variable	Model [1] # restaurants	Model [2] # cuisines	Model [3] HV	Model [4] Rarity
Gini index (in log)	2.410 ***	1.099 ***	0.024 **	0.463 **
	(0.376)	(0.250)	(0.010)	(0.219)
Mean income (in log)	0.992 ***	0.800 ***	0.005	0.166
	(0.252)	(0.174)	(0.007)	(0.147)
Area (in log)	0.109 ***	0.015	−0.005 ***	−0.028 *
	(0.025)	(0.017)	(0.001)	(0.015)
Ethnic diversity	1.280 ***	0.499 ***	0.031 ***	0.362 ***
	(0.208)	(0.104)	(0.005)	(0.113)
Population size (in log)	2.498 ***	2.018 ***	0.042 ***	0.610 ***
	(0.304)	(0.217)	(0.009)	(0.189)
Tourism (in log)	0.111 ***	0.071 ***	0.001 ***	0.029 ***
	(0.005)	(0.005)	(0.000)	(0.003)
In-commuters (in log)	0.354 ***	0.308 ***	0.004 ***	0.137 ***
	(0.036)	(0.024)	(0.001)	(0.020)
Out-commuters (in log)	−2.286 ***	−1.875 ***	−0.034 ***	−0.557 ***
	(0.293)	(0.209)	(0.009)	(0.184)
Average household size (in log)	−0.364	−0.708 ***	−0.002	−0.193
	(0.336)	(0.269)	(0.009)	(0.190)
Share population aged 15-29	2.565	3.831 ***	0.236 ***	1.818 *
	(1.915)	(1.272)	(0.051)	(1.102)
Share population aged 30-44	11.366 ***	9.195 ***	0.408 ***	4.891 ***
	(2.237)	(1.607)	(0.060)	(1.297)
Share population aged 45-59	7.678 ***	5.722 ***	0.187 ***	3.238 ***
	(1.563)	(1.266)	(0.042)	(0.915)
Share population aged 60-74	5.724 ***	3.625 ***	0.177 ***	1.771 *
	(1.709)	(1.371)	(0.045)	(0.975)
Share population aged ≥ 75	1.398	0.604	0.187 ***	0.889
	(1.702)	(1.307)	(0.045)	(0.967)
# H & M stores (+1; in log)	0.250 *	0.011	0.029 ***	−0.029
	(0.136)	(0.051)	(0.004)	(0.087)
Constant	−19.748 ***	−15.936 ***	−0.266 ***	−5.143 ***
	(3.038)	(2.190)	(0.083)	(1.786)
Observations	2,360	2,360	1,876	1,876
Pseudo R^2	0.215	0.529		
R^2			0.499	0.352
Method	Negative binomial	Poisson	OLS	OLS

Notes: Standard errors are reported in parentheses. *** significant at 1 %, ** significant at 5 %, * significant at 10 % level.

Table A.12: Regression results on product variety based on circular markets with "unknown" cuisines considered as Austrian cuisine

Dependent variable	Model [1] # restaurants	Model [2] # cuisines	Model [3] HV	Model [4] Rarity
Educational Gini-index (in log)	2.034 ***	2.049 ***	0.029 ***	4.472 ***
	(0.075)	(0.051)	(0.003)	(0.239)
Mean years of education (in log)	6.296 ***	2.372 ***	0.007	7.555 ***
	(0.137)	(0.064)	(0.005)	(0.470)
Ethnic diversity	1.125 ***	0.046 ***	0.038 ***	1.675 ***
	(0.020)	(0.008)	(0.001)	(0.069)
Population size (in log)	0.500 ***	0.317 ***	0.013 ***	1.051 ***
	(0.005)	(0.003)	(0.000)	(0.016)
Tourism (in log)	0.086 ***	0.038 ***	0.001 ***	0.153 ***
	(0.001)	(0.001)	(0.000)	(0.004)
In-commuters (in log)	0.043 ***	0.007 ***	0.002 ***	0.180 ***
	(0.005)	(0.002)	(0.000)	(0.018)
Out-commuters (in log)	−0.227 ***	−0.034 ***	−0.004 ***	−0.112 ***
	(0.006)	(0.003)	(0.000)	(0.021)
Average household size (in log)	−0.400 ***	−1.255 ***	−0.004	0.426 *
	(0.068)	(0.047)	(0.003)	(0.239)
Share population aged 15-29	−5.447 ***	−5.143 ***	−0.268 ***	−2.441 **
	(0.274)	(0.151)	(0.011)	(1.008)
Share population aged 30-44	5.255 ***	−6.498 ***	0.111 ***	22.044 ***
	(0.392)	(0.233)	(0.016)	(1.397)
Share population aged 45-59	0.382	−4.022 ***	0.051 ***	19.557 ***
	(0.301)	(0.204)	(0.012)	(1.094)
Share population aged 60-74	−0.735 **	−5.504 ***	−0.169 ***	6.482 ***
	(0.342)	(0.199)	(0.014)	(1.225)
Share population aged ≥ 75	−5.778 ***	−7.286 ***	−0.092 ***	−2.652 **
	(0.342)	(0.233)	(0.014)	(1.215)
# H & M stores (+1; in log)	0.453 ***	0.100 ***	0.025 ***	−0.040
	(0.009)	(0.004)	(0.000)	(0.032)
Constant	−11.844 ***	3.338 ***	0.084 ***	−24.731 ***
	(0.525)	(0.302)	(0.020)	(1.759)
Observations	24,421	24,421	24,421	24,421
Pseudo R^2	0.214	0.853		
R^2			0.920	0.842
Method	Negative binomial	Poisson	OLS	OLS

Notes: Circular markets are defined for each restaurant by drawing a radius of 5 km around the restaurant's location. Standard errors are reported in parentheses. *** significant at 1 %, ** significant at 5 %, * significant at 10 % level.

Online-Only Appendix

Table OA.1: Regression results on product variety based on municipal markets with income inequality in levels

Dependent variable	Model [1] # restaurants	Model [2] # cuisines	Model [3] HV	Model [4] Rarity
Gini index	5.885 ***	2.642 ***	0.084 ***	1.085 **
	(0.914)	(0.591)	(0.030)	(0.548)
Mean income (in log)	0.982 ***	0.743 ***	0.005	0.057
	(0.252)	(0.173)	(0.008)	(0.151)
(Pseudo) R^2	0.215	0.525	0.587	0.319
Theil index	2.848 ***	1.423 ***	0.048 ***	0.701 ***
	(0.460)	(0.306)	(0.015)	(0.271)
Mean income (in log)	0.892 ***	0.675 ***	0.004	0.039
	(0.252)	(0.175)	(0.008)	(0.151)
(Pseudo) R^2	0.214	0.526	0.587	0.320
Atkinson index	7.303 ***	3.382 ***	0.114 ***	1.199
	(1.225)	(0.789)	(0.040)	(0.733)
Mean income (in log)	0.991 ***	0.748 ***	0.005	0.057
	(0.253)	(0.173)	(0.008)	(0.151)
Pseudo R-squared	0.214	0.525	0.587	0.319
(Pseudo) R^2	0.214	0.525	0.587	0.319
90/10 quantile ratio	0.032 ***	0.013 **	0.000	−0.003
	(0.009)	(0.006)	(0.000)	(0.005)
Mean income (in log)	1.072 ***	0.869 ***	0.006	0.018
	(0.257)	(0.173)	(0.008)	(0.154)
(Pseudo) R^2	0.212	0.524	0.585	0.318
80/20 quantile ratio	0.051	0.023	0.000	−0.013
	(0.043)	(0.024)	(0.001)	(0.025)
Mean income (in log)	0.987 ***	0.850 ***	0.004	0.022
	(0.257)	(0.174)	(0.008)	(0.154)
(Pseudo) R^2	0.212	0.524	0.585	0.318
90/50 quantile ratio	0.868 ***	0.434 ***	0.015 ***	0.251 ***
	(0.135)	(0.099)	(0.004)	(0.080)
50/10 quantile ratio	−0.028	−0.030	−0.001	−0.044 ***
	(0.030)	(0.023)	(0.001)	(0.017)
Mean income (in log)	1.064 ***	0.734 ***	0.005	0.004
	(0.256)	(0.176)	(0.008)	(0.154)
(Pseudo) R^2	0.215	0.526	0.588	0.323
Observations	2,360	2,360	1,876	1,876
Additional Controls	yes	yes	yes	yes
Method	Negative binomial	Poisson	OLS	OLS

Notes: Standard errors are reported in parentheses. *** significant at 1 %, ** significant at 5 %, * significant at 10 % level. Model [1] and Model [2] report the Pseudo R^2 statistic, while Model [3] and Model [4] report the standard R^2.

Table OA.2: Regression results on product variety based on circular markets with income inequality in levels

Dependent variable	Model [1] # restaurants	Model [2] # cuisines	Model [3] HV	Model [4] Rarity
Educational Gini index	19.670 ***	17.262 ***	0.663 ***	39.793 ***
	(0.646)	(0.422)	(0.032)	(2.137)
Mean years of education (in log))	6.023 ***	2.340 ***	−0.026 ***	6.253 ***
	(0.137)	(0.064)	(0.007)	(0.473)
Observations	24,424	24,424	24,424	24,424
(Pseudo) R^2	0.215	0.853	0.919	0.838
Educational Theil index	65.301 ***	52.765 ***	2.412 ***	131.025 ***
	(2.063)	(1.270)	(0.105)	(7.000)
Mean years of education (in log)	6.162 ***	2.551 ***	−0.023 ***	6.605 ***
	(0.135)	(0.063)	(0.007)	(0.469)
Observations	24,424	24,424	24,424	24,424
(Pseudo) R^2	0.215	0.853	0.919	0.838
Educational Atkinson index	70.552 ***	55.414 ***	2.505 ***	135.143 ***
	(2.170)	(1.335)	(0.110)	(7.378)
Mean years of education (in log)	5.779 ***	2.169 ***	−0.035 ***	6.005 ***
	(0.138)	(0.066)	(0.007)	(0.478)
Observations	24,424	24,424	24,424	24,424
(Pseudo) R^2	0.215	0.853	0.919	0.838
90/10 education quantile ratio	0.458 ***	0.277 ***	0.011 ***	1.164 ***
	(0.034)	(0.018)	(0.002)	(0.114)
Mean years of education (in log)	5.559 ***	2.459 ***	−0.026 ***	4.510 ***
	(0.175)	(0.076)	(0.009)	(0.606)
Observations	24,424	24,424	24,424	24,424
(Pseudo) R^2	0.213	0.851	0.917	0.836
80/20 education quantile ratio	0.354 ***	0.011	0.005 ***	0.333 ***
	(0.026)	(0.010)	(0.001)	(0.097)
Mean years of education (in log)	6.206 ***	3.095 ***	0.001	7.814 ***
	(0.147)	(0.076)	(0.008)	(0.507)
Observations	24,424	24,424	24,424	24,424
(Pseudo) R^2	0.213	0.851	0.917	0.836
90/50 education quantile ratio	0.498 ***	0.424 ***	0.011 ***	1.257 ***
	(0.050)	(0.028)	(0.003)	(0.171)
50/10 education quantile ratio	−3.600 ***	−2.313 ***	−0.089 ***	−7.523 ***
	(0.147)	(0.107)	(0.007)	(0.474)
Mean years of education (in log)	6.865 ***	2.693 ***	0.014	8.018 ***
	(0.177)	(0.077)	(0.009)	(0.626)
Observations	24,424	24,424	24,424	24,424
(Pseudo) R^2	0.215	0.852	0.918	0.839
Additional Controls	yes	yes	yes	yes
Method	Negative binomial	Poisson	OLS	OLS

Notes: Circular markets are defined for each restaurant by drawing a radius of 5 km around the restaurant's location. Standard errors are reported in parentheses. *** significant at 1 %, ** significant at 5 %, * significant at 10 % level. Model [1] and Model [2] report the Pseudo R^2 statistic, while Model [3] and Model [4] report the standard R^2.

Table OA.3: Regression results on product variety based on municipal markets using differences (rather than ratios) between income percentiles

Dependent variable	Model [1] # restaurants	Model [2] # cuisines	Model [3] HV	Model [4] Rarity
Difference between income in q90 and q10 (in logs)	0.983 ***	0.461 ***	0.013 *	0.021
	(0.225)	(0.146)	(0.007)	(0.134)
Mean income (in log)	0.114	0.387 *	−0.006	0.020
	(0.317)	(0.222)	(0.010)	(0.184)
(Pseudo) R^2	0.213	0.525	0.585	0.318
Difference between income in q80 and q20 (in logs)	0.653 ***	0.325 **	0.009	−0.068
	(0.230)	(0.146)	(0.007)	(0.135)
Mean income (in log)	0.453	0.554 ***	−0.003	0.084
	(0.308)	(0.213)	(0.010)	(0.178)
(Pseudo) R^2	0.212	0.524	0.585	0.318
Difference between income in q90 and q50 (in logs)	1.112 ***	0.540 ***	0.016 ***	0.226 **
	(0.177)	(0.126)	(0.006)	(0.104)
Difference between income in q50 and q10 (in logs)	−0.945 ***	−0.546 **	−0.019 **	−0.563 ***
	(0.297)	(0.253)	(0.009)	(0.171)
Mean income (in log)	0.905 **	0.788 ***	0.007	0.343 *
	(0.357)	(0.262)	(0.011)	(0.205)
(Pseudo) R^2	0.215	0.525	0.587	0.322
Observations	2,360	2,360	1,876	1,876
Additional Controls	yes	yes	yes	yes
Method	Negative binomial	Poisson	OLS	OLS

Notes: Standard errors are reported in parentheses. *** significant at 1 %, ** significant at 5 %, * significant at 10 % level. Model [1] and Model [2] report the Pseudo R^2 statistic, while Model [3] and Model [4] report the standard R^2.

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