Segmentation of Consumer Markets in the U.S.: What Do Intercity Price Differences Tell Us?

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Abstract

We quantify the magnitude of market segmentation in U.S. consumer market, and explore the underlying factors generating this segmentation, using a quarterly panel of retail prices for 45 products in 48 U.S. cities from 1985 to 2009. The extent of market segmentation is estimated using both linear autoregressive (AR) and nonlinear threshold autoregressive (TAR) models. We find wide variation in market segmentation across both cities and products. Contrary to a widespread perception, market segmentation is not necessarily larger for non-tradable services compared to tradable goods. We identify potential drivers of market segmentation by relating the cross-city and cross-product variations of market segmentation to location-specific and product-specific characteristics - distance, relative city sizes, relative incomes, type of product and proximity to marketplace. Distance, which captures more than transport costs, turns out to be most important factor even after taking a range of other potential factors into account, casting doubt on the "death of distance" hypothesis. The effect of distance, however, varies by product characteristic such that greater distance generates significantly higher levels of market segmentation for perishable products and products that are not locally produced.

Keywords: Market segmentation, Price differences, Bandwidth, TAR model, U.S. cities, Distance, Product characteristics.

JEL Classification Numbers: E31,F15,L16,R12

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1 Introduction

Are consumer markets in the U.S. integrated? Given that markets are said to be integrated if they are connected with low barriers to trade, standard empirical practice has been to use price differentials, or dispersion of prices, across locations as plausible measure of market segmentation. In highly integrated markets, therefore, prices for similar products in different cities should not be very different (e.g., Engel and Rogers 2004).[1] On the flipside, persistent and large cross-region price differences for (virtually) identical products run counter to the notion of market integration, and has been the subject of great interest to policymakers.[2] Yet little is known about to what extent markets are segmented, in particular how markets are segmented along various products, mainly due to the lack of appropriate metric of market segmentation. Moreover, consensus has yet been reached about underlying factors behind market segmentation.

The primary objectives of this study are twofold. We first quantify the magnitude and persistence of market segmentation by utilizing information on price differences within the framework of popular time series models. We then explore the factors accounting for the market segmentation across both locations and products. To this end, we use individual retail price data from the American Chamber of Commerce Researchers Association (ACCRA) for 45 consumer products in 48 major U.S. cities over the twenty five year period 1985 to 2009. With a wide geographic dispersion, cities in the U.S. could provide deeper information on the extent of consumer market segmentation for various products.[3] The ACCRA data are the actual retail prices of items such as a pound of beef steak of USDA choice grade, a specific brand of men's shirt and a 2-liter bottle of Coca Cola, as well as the prices of selected services - apartment rents, a man's haircut, dry cleaning, to name a few - that are conventionally considered non-tradables. In turn, the data allow us to calculate actual

[1] When markets are perfectly competitive and firms have no market power, the law of one price (LOP) prevails in the absence of transport costs, taxes, and price discrimination (e.g., Stole 2007).

[2] According to Hsieh and Moretti (2015), a significant spatial dispersion of wages found across U.S. states, driven by worker productivity differences, reflects an inefficient spatial allocation of resources and an output loss. This is particularly the case for currency union where prices in different economies are quoted in a single common currency. As clearly noted in the European Commission statement (1999) that *"the single currency can squeeze price dispersion in EU markets"*, the adoption of a single currency in the Eurozone (EZ) was to enhance market integration by removing trade barriers and eventually by reducing transaction costs.

[3] In addition, use of intra-national price data permits us to get around the potential effects of cross-country factors such as tariffs and nominal exchange rates on the inference on market segmentation. In principle, with reduced barriers to trade and mobility, fixed exchange rates and monetary and fiscal union, cities within U.S. are expected to allow the forces of arbitrage to eliminate price differentials for consumer products. In practice, however, prices are quite different between geographically distant locations even for goods sold online (e.g., Gorodnichenko and Talavera 2011, Boivin et al. 2010). For a dissenting view, see Cavallo et al. (2014) who document that the law of one price (LOP) holds in the EZ.

price differences for narrowly defined products, which is crucial for measuring the extent of market segmentation. Since price differences across location are not stable but instead fluctuate over time, static measures of market segmentation based on price comparisons at a given point of time are not very appealing. A better way to quantify the extent of market segmentation across cities utilizes the information embedded in the dynamic behavior of the inter-city price differentials.

Accordingly, we employ a couple of popular time series models that are well suited to this purpose: non-linear band Threshold Autoregressive (TAR) models and linear Autoregressive (AR) models. Originally motivated by the presence of transaction costs, a TAR model is a natural choice when modeling the behavior of price differentials between retail markets. The underlying intuition of this model is that long run prices in two spatially separated markets may differ in the presence of inherent transaction costs, such as transport costs and taxes, which drive a wedge between the prices and limit arbitrage opportunities. In consequence, an inter-city price differential tends to persist if it falls within a certain band, while it is mean reverting back to this band if the differential falls outside the band. The estimated 'band of inaction' or bandwidth (BW) within which relative prices follow a random walk process is thus an appropriate measure of the extent of market segmentation in the long run. In the current study, we estimate asymmetric band TAR models, which allow the dynamics of the relative prices to differ above and below the 'band of inaction'. Although previous studies have focused on transport costs as the major source of the inaction band in TAR models, more recent studies (e.g., O'Connell and Wei 2002, Anderson and van Wincoop 2004) show that the band of inaction may also be generated by additional factors including differences in local distribution costs, taxation, market power and markups.[4] In this vein, the notion of bandwidth (BW) is also applicable to non-traded services, for which transportation costs should matter little. As an alternative measure of market segmentation, we also utilize the long-run average price differences (LAPD) estimated from linear AR models (e.g., Ceglowski 2004, Goldberg and Verboven 2005). We present the LAPD results alongside the BW results as a robustness check for two reasons. Firstly, AR model based measures of market segmentation are widely used in the literature. Secondly, and possibly more importantly, our tests for the linearity of intercity price differential dynamics do not yield conclusive evidence on nonlinearity, so it is informative to compare the results from the measures based on both AR and TAR models.

[4] Moreover, Friberg and Martensen (2001) illustrate that greater arbitrage barriers can be endogenously introduced by firms to increase the degree of market segmentation.

Another appealing feature of the use of the ACCRA retail price dataset is that it enables us to carry out a regression analysis identifying the location and product specific factors generating market segmentation. To be specific, our BW and LAPD metrics of market segmentation are regressed onto a set of candidate product and city-pair specific explanatory variables characteristics, including product types and proximity of production to marketplace, distance - generally viewed as a proxy for transport costs - and differences in incomes and city sizes. Consideration of these factors is mainly governed by the fact that markets are segmented in both geographical and product dimensions. On geographic dimension, both theory and the empirical literature emphasize the key role of distance or transport costs in generating market segmentation. Income differentials may also play a role in market segmentation in view of the link between price and income levels set out in the Harrod-Balassa-Samuelson (HBS) hypothesis and the pricing-to-market (PTM) hypothesis (e.g., Atkeson and Burstein 2008, Alessandria and Kaboski 2011, Simonovska forthcoming). Higher city-level incomes tend to generate higher consumer prices through higher wage rates and other local costs (e.g., rent), which are closely related to local income levels. Labor market segmentation may also lead to segmentation in product markets through income, wage and local distribution costs channels. City size differences, often proxied by population or population density differences, may also help explain market segmentation since larger cities, typically with more competitive market environments, are likely to have lower markups and hence lower prices (e.g., Handbury and Weinstein 2014, Melitz and Ottaviano 2008).[5]

Our work, built on a long literature studying dynamics of relative prices, is closely related to O'Connell and Wei (2002) who employed a similar ACCRA data set (for 24 U.S. cities over the period 1975:Q1-1992:Q4) and examined the pattern of mean reversion of intercity price differences within the framework of linear and nonlinear time series models. Although they also estimate absolute deviation from LOP in TAR and AR models, their focus rests on finding evidence of mean reversion *per se* instead of quantifying the extent of market segmentations. Besides they do not identify potential driving forces behind the observed intercity price differentials.

We find a significant amount of market segmentation within the U.S. as the inter-city price differentials are non-negligible and persist over time. The extent of market segmentation in terms of BW and LAPD varies widely both across the 45 products and across city pairs for each product.

[5] If markets are segmented, prices in each market are set as being equal to marginal cost times a markup that ultimately hinges on factors like income levels and market competition, which is an instance of third-degree price discrimination.

The average BW estimated from more than 50,000 TAR models exhibits a large dispersion across products, ranging from 5.9 percent for a *McDonald's Hamburger* to 28.2 percent for *Potatoes*. The substantial variation of market segmentation is also noted across the 1,128 city pairs within each product. Surprisingly, the BW measure of market segmentation is not necessarily larger for non-tradeable services compared to traded goods, casting doubt on the widely held view that prices differentials are higher for products that are less traded. A qualitatively similar picture is painted when the alternative metric of market segmentation, LAPD, is used, although the two metrics of market segmentation match more closely at the city-level than at the product level.

When we parse out potential contributors to the market segmentations, we find that distance is the most salient factor. Market segmentation is greater (i.e., BW and LAPD are larger) for city-pairs that are farther apart, even after controlling for differences in real incomes and city sizes. Distance is also the key factor explaining the level of market segmentation in "non-tradeable" services, although the size of the effect is smaller than for goods. Relative city-size, measured by population differences, also turns out to be significant for explaining market segmentation in some products, but not in all. Real income gaps, however, turn out to have little explanatory power.

More importantly, we notice that the quantitative effect of distance on market segmentation varies considerably across products, and hinges critically upon the types of product and the proximity of market to production center. *Ceteris paribus* an increase in distance between markets exerts a greater impact on market segmentation in the products that are either more tradable or produced not locally. When we further break down the distance effect into the part attributable to transport cost and the remaining part due to non-transport cost along the lines of Choi and Choi (2014), we find that both components are significant for traded products, while only the non-transport costs component is significant in the non-traded service. This suggests that markets for non-traded services are mainly segmented by non-trade cost factors such as local costs or markups, rather than by transport costs. We also find some evidence of state border effect on market segmentation, as the size of market segmentation for city-pairs in the same state tend to be smaller.

The remainder of this paper is structured as follows. The next section briefly outlines the data used in the paper and presents some preliminary analysis of the time properties of the price differential data. The unit root and linearity tests are also conducted in this section to model the dynamics of inter-city price differentials. Section 3 lays out the two metrics of market segmentation - BW and LAPD - and their relevance to characterizing the dynamic behavior of inter-city price differentials is explained. Section 4 contains our regression analysis, where we identify and quantify the main determinants of the observed price differentials across cities and products. Section 5 concludes the paper. The Appendix contains a detailed description of the data.

2 Data and descriptive statistics

2.1 The Data

We use actual retail prices of individual goods and services collected from publications issued by the American Chamber of Commerce Researchers Association (ACCRA), *Cost of Living Index*. Prices are quoted inclusive of all sales taxes levied on the products (state, county, and local) and many jurisdictions subject many food products to a lower rate of tax or exempt it altogether. The data set, albeit with different sample spans, was also employed in a number of prior related studies (e.g., Parsley and Wei 1996, O'Connell and Wei 2002, Crucini et al. 2012). After dropping price series with missing observations for more than two consecutive quarters[6], we end up with price data for 45 goods and services for 48 cities that appeared in roughly 90 percent of the quarterly surveys between 1985.Q1 and 2009.Q4. Our panel data set, spanning 25 years of the Great Moderation during which both the level and volatility of inflation remain stable, encompasses a wide spectrum of products that are more comprehensive than those employed in the previous studies.[7] Since the results on relative prices are sensitive to the choice of numeraire (e.g., Cecchetti et al., 2002), we consider all pair-wise combinations of cities in the set of prices by setting every city as a base city, resulting in 50,760 time series of inter-city price differentials (1,128 ($= \frac{48\times 47}{2}$) city pairs for 45 products). In the regression analysis, we augment our price data with city-level income and population data, as well as product specific characteristics, which are extracted from the various sources isted in Table A.2 in the Appendix.

A notable merit of our data is that we rely on information available for a broader range of

[6] Following Parsley and Wei (1996, p.1213-15) and O'Connell and Wei (2002, p.35-6), we linearly interpolate missing values in constructing the dataset. A missing observation that is not continuous is therefore replaced with the centered two-quarter average value. Although interpolation may affect dynamic behavior of time series, we view that it is not much consequential to our analysis partly because data were interpolated for a very short period only (no more than two quarters) and more because the literature suggests that the information set of the interpolated data is similar to the information set of the original data (e.g., Sarno et al. 2004). Our conclusions are virtually unaltered by using nonlinear interpolation methods.

[7] Parsley and Wei (1996) adopted 51 goods and 48 cities and O'Connell and Wei (2002) studied 48 products for 24 cities over the period 1975.Q1-1992.Q4 that encompasses both the Great Inflation and the Great Moderation periods. In their recent study, Crucini et al. (2012) used a comparable data set to ours covering 48 products and 52 cities, but with a much shorter data span of 1990-2007.

consumer products, including services. As described in Table A.1 in the Appendix, the products included in our dataset range broadly from basic food products such as *Bread* and *Eggs*, to manufacturing goods like *Detergents* and *Tissues*, and to services including *Medical Service* and *Hairstyling*. Following the convention in the literature (e.g., Parsley and Wei 1996), we group these products into large categorical classifications based on product types, such as perishables (P), non-perishables (N) and services (S) as represented in the third column of Table A.1. In the spirit of O'Connell and Wei (2002), we also classify them into three groups based on the proximity of production to the marketplace as a proxy measure of the markup rate: Category A (not locally-produced), Category B (may be locally-produced) and Category C (locally-produced). As discussed below, these product categories are used in our regression analysis to identify product characteristics that are conducive to market segmentation.

Our dataset is well suited for addressing the key questions at hand on several dimensions. First, product homogeneity is a critical feature in the study of spatial segmentation of markets. These survey prices are known to be quite comparable across cities because they are very specific in terms of quality (brand) and quantity (package), such as *Steak* (one pound, USDA Choice), *Soft Drink* (two liters, Coca Cola), *Gasoline* (one gallon, regular unleaded), and *Beauty Salon* (woman's shampoo, trim, and blow dry). The specificity of product definition enhances price comparability across geographic locations and highlights the role of price differentials in explaining market segmentation. Since the data are absolute prices for specific goods and services collected in a consistent manner by a single agency, we not only can assess the absolute size of price differences between locations, but also we can pin down the exact location of the mean of relative prices toward which the price differences converge. Of particular value to our dataset is a more extensive geographical coverage than other datasets that were popularly used in the literature, such as the BLS micro-data and grocery store scanner data. The wide geographic distribution of 48 cities (markets, see Table A.3) around the U.S. generates a number of time series for intercity relative prices that makes meaningful cross-sectional regression analysis possible in identifying potential determinants of market segmentation at the level of city-pairs. Another attractive feature of our data is that the sample covers a relatively long time span, 1985 to 2009, which is crucial for reliable time series modeling of the price dynamics.[8]

[8] A clear trade-off exists between data span and data coverage as the number of cities with available data reduces to just 22 if we start the sample from 1976. Since the focus of our study rests on the cross-product variation in inter-city relative prices, we choose the breadth of coverage in terms of available cities and products over the length of time. By focusing on the post-1985 period, we intend to minimize the nontrivial influence of the so-called Great Inflation on the dynamic behaviors of individual good prices in the U.S. Inter-city relative prices might have experienced structural

With that said, our dataset is not without limitations. One drawback of the dataset, especially compared to the BLS data, is that the product coverage is not as comprehensive as disaggregated price indices.[9] Another limitation of our data is possible measurement errors from using a less rigorous sampling methodology and quality of data collection. Although not perfect, our data set is particularly well suited for analyzing the central topic of this study with a clear edge over the alternative datasets in terms of the locational coverage for homogeneous products.

2.2 Descriptive statistics of intercity price differences

Before proceeding to measuring the size of market segmentation, it is useful to examine the magnitude and dispersion of the intercity price differentials by products. The price differentials are measured as $q^k_{ijt} = |p^k_{it} - p^k_{jt}|$ where p^k_{it} is the log of the price of product k at time t in city i. Table 1 reports summary statistics (mean, median, 10^{th}- and 90^{th}-percentiles and standard deviations) for the absolute values of the 1,128 city-pair price differentials for each product. A couple of remarks are in order. First, there exist non-trivial differentials of intercity price across products with the mean absolute price difference ranging from 6% (*McDonald's Hamburgers*) to 25.7% (*Newspapers*), indicating that prices hardly converge in an absolute sense. The price difference appears to be on average larger in services that are conventionally recognized as nontradables probably because they are inherently less homogeneous across geographic locations. Considerable city-pair price gap, however, is noticed even in the products that are easily tradable across locations, especially in some grocery items. For example, the average absolute price difference is as large as 24% for *Potatoes* and 22% for *Bread*, whereas it is merely 6% for *McDonald's Hamburgers* and 7.3% for *Gasoline*.[10] This non-negligible size of average intercity price difference observed in some conventional traded products implies that tradability alone may not fully account for the intercity price differences.

Second, our results highlight the considerable variation in market segmentation across city-pairs within products. Take *Bread* for example, the 10^{th}- and 90^{th}-percentiles of city-pair price gap are 13.2% and 33.7%, respectively, leading to the difference between the 90^{th} and 10^{th} percentiles of exceeding 20 percentage point. Moreover, the dispersion of intercity price gap varies widely across

breaks at the onset of the Great Moderation.

[9] The ACCRA data and the BLS data are somewhat different in the coverage of commodities and the geographic boundaries. Despite the difference, the two datasets are known to produce quite similar results (e.g., Schoeni 1996).

[10] Recall that our retail prices are inclusive of local sales taxes, which may vary across time and space. Interestingly the 6-7 percent BWs are very close to the average local tax rates of 6.5 percent in the U.S. (Cavallo et al. 2014, footnote 7).

products. The difference between the 90^{th} and 10^{th} percentiles of intercity price gap reaches more than 30 percentage point for *Newspapers*, while it is less than 5 percentage point for *McDonald's Hamburgers*, suggesting that the dispersion of intercity price gap is smaller for more homogeneous goods than for intrinsically more heterogeneous service products. Even among relatively homogeneous products such as *Potatoes* and *Margarine*, however, quite a wide cross-city dispersion is noted. This sentiment is confirmed by the cross-city dispersion (measured by standard deviations) of the intercity price differences as they differ substantively across products, ranging from 0.054 (*Gasoline*) to 0.166 (*Potatoes*). Our results therefore lend credence to the argument that consumer markets in the U.S. are non-trivially segmented and the extent of market segmentation varies considerably across products as well as across city-pairs.

A visual representation of this message is conveyed in Figure 1 where the empirical distributions of annualized inter-city price differentials (q^k_{ijt}) are plotted in each year of the sample period. On closer inspection, the graph suggests that the inter-city price differentials are roughly symmetrically distributed around zero in all products throughout the sample period, and that the dispersion of the differentials has not narrowed over time, indicative of the persistence of price differences. Evidently, the breadth of distribution differs substantively across products, with a wider distribution for service products, such as *Apartment Rents* (Item 32), *Beauty Salon* (Item 40), and *Newspapers* (Item 43), compared to conventional tradable goods like *Gasoline* (Item 26) and *McDonald's Hamburgers* (Item 12). This confirms the near consensus formed in the LOP literature that the distribution of LOP deviations are generally centered around zero and it is more dispersed for the goods that are less tradable and that use more nontraded inputs to produce (e.g., Crucini et al. 2005). More importantly, the distributions of the inter-city price differentials appear to be quite stable over time for in almost all of the products, lending little support to the notion of time-varying market segmentation.

2.3 Testing for mean-reversion and linearity of intercity price differentials

Our preliminary data analysis in the previous subsection suggests that retail price differentials across U.S. cities are non-negligible and persist over time. They also vary systematically by product. Given the persistent price differentials, it is instructive to examine whether a certain mean level exists toward which the price differences revert over time, or they move further away from it. If price differentials are mean-reverting toward a non-zero mean level, then the nonzero long-run mean can be viewed as the extent of market segmentation because it does not disappear over time. It is equally important to establish whether the mean-reverting patterns are better characterized by nonlinear or linear dynamic models. Prior to quantifying the magnitude of market segmentation based on proper time series models, therefore, we test for the stationarity and the linearity of inter-city price differentials .

To probe whether or not inter-city price differentials are reverting toward certain mean levels, we first implement two popular unit-root tests, the ADF test and the DF-GLS test under the null hypothesis of unit-root nonstationarity. The left-hand panel of Table 2 reports the frequencies of the rejection of unit-root null hypothesis out of 1,128 city-pairs in each product at the ten percent significance level. Our results seem to yield some evidence of mean reversion in inter-city price differentials, but the evidence is not conclusive enough due to the wide range of the rejection frequencies, 34.5%-69.6% (the ADF test) and 36.5%-76.7% (the DF-GLS test). This lack of conclusive evidence on mean-reversion, however, could result from stationary but nonlinear behavior of intercity price differentials as illustrated by Choi and Moh (2006). Put differently, the relatively low frequencies of rejection rates might have been driven by nonlinear but stationary dynamics of inter-city price differentials, such as TAR models.

This leads us to explore whether nonlinearity is statistically significant in characterizing the movements of inter-city price differentials when tested against a linear model specification. We here consider three popular tests, Tsay's (1989) test, Dahl and Gonzalez-Rivera's (2003) LM test and Hansen's (1997) test, under the null hypothesis of a linear AR model against the alternative of threshold-type nonlinearity. As presented in the right-hand panel of Table 2, our results seem to yield some evidence of nonlinearity but the frequencies of rejecting the null hypothesis of linear model (at 10% significance level) are not high enough to draw any firm conclusion on the nonlinearity. The average rejection rates of the three tests are all below 50%. Moreover, the rejection frequencies vary widely across products ranging from 25.7% to 80.2%. Although there seem to be compelling theoretical reasons for relative prices to be intrinsically nonlinear, it would be a step into the right direction to consider both linear and nonlinear models in extracting information concerning market segmentation, in light of the mixed evidence on the nonlinearity.[11]

[11] Using a similar ACCRA data set but with a different sample period, however, O'Connell and Wei (2002) conclude that the nonlinear TAR model specification provides a superior characterization of the data over the usual linear AR models.

3 Two metrics of market segmentation

Intuitively, price differentials between locations which do not disappear in the long run reflect market segmentations. Given the mixed evidence on the linearity, we consider a couple of competing time series models within which the extent of market segmentation is quantified by utilizing the information on long-lasting price differentials. They are nonlinear TAR model and linear AR model. Both models offer intriguing intuition on measuring market segmentations and thus are adopted here.

3.1 Asymmetric band-TAR model and bandwidth (BW)

In the presence of transaction costs and price shocks, price differentials across markets will tend to persist unless they exceed the associated transaction costs. A band of inaction is therefore created such that price differentials between locations tend to revert toward mean outside the band where arbitrage is profitable, while there is no tendency toward the mean-reversion inside the band where transaction cost outweighs the potential arbitrage profit. The adjustment of the price differentials towards the band therefore occurs in a nonlinear fashion.[12] As noted earlier, however, the band of inaction can be generated by various types of market segmentations - such as trade costs, taxes, and local distribution costs - as well as transport costs, given that arbitrage within a country is unhindered by policy-imposed trade barriers or exchange rate fluctuations.

Here we implement the following asymmetric Band-TAR model, with special interest placed on the key parameters of the thresholds (τ_L^k, τ_U^k).

$$\Delta q_{ij,t}^k = \begin{cases} \tau_U^k(1-\beta^k) - (1-\beta^k)q_{ij,t-1}^k + \sum_{h=1}^m \beta_{h,ij}^k \Delta q_{ij,t-h}^k + \varepsilon_{ij,t}^k & \text{if } \tau_U^k < q_{ij,t-1}^k \\ \varepsilon_{ij,t}^k & \text{if } \tau_L^k \le q_{ij,t-1}^k \le \tau_U^k \\ \tau_L^k(1-\gamma^k) - (1-\gamma^k)q_{ij,t-1}^k + \sum_{h=1}^m \gamma_{h,ij}^k \Delta q_{ij,t-h}^k + \varepsilon_{ij,t}^k & \text{if } q_{ij,t-1}^k < \tau_L^k \end{cases} \quad (1)$$

where $q_{ij,t}^k$ denote the (log) price differential of good k between cities i and j at time t ($ln(P_{it}^k) - ln(P_{jt}^k)$) and $\varepsilon_{ij,t}$ represents the error term that could be heteroskedastic. This model implies that relative prices exhibit mean-reversion outside the band, while they follow a random walk process within the band where no adjustment takes place. Since τ_U^k and τ_L^k denote the upper and lower

[12] Under the assumption of discrete changes in regimes, the TAR model is known to be particularly suitable for describing the nonlinear behavior of relative prices at the individual good level. The smooth transition autoregressive (STAR) model is known to better characterize the nonlinear behavior of relative prices using price indices for a basket of goods and services (e.g., Michael et al. 1997, Taylor and Taylor 2004). The main distinguishing feature of the two types of model is that the STAR model assumes a smooth transition of price differences between regimes while the TAR model assumes that the adjustment between regimes takes place discretely.

bounds of the inaction band, the width of inaction band or bandwidth is measured by $[\tau_L^k, \tau_U^k]$ and hence zero bandwidth reflects fully integrated markets (e.g., Sarno et al. 2004).[13] Note that in this model the dynamics of the process outside the threshold could be different depending on whether deviations occur above or below the threshold band. γs and βs measure the speeds at which the relative prices revert back to the band once they cross the lower and upper thresholds of the band.

With retail prices for 45 products in 48 cities spanning 1985.Q1 to 2009.Q4, we estimate more than 50,000 asymmetric TAR models based on a grid-search on the threshold parameters. The left-hand side of Table 3 (columns 1-5) reports the summary statistics of market segmentation by product - mean, median, 5^{th}- and 95^{th}-percentiles of BW ($\hat{\tau}_U^k - \hat{\tau}_L^k$), along with the half-lives outside of the inaction bands, estimated from the 1,128 city-pairs for each product.

The results illustrate several points. First, the estimated BWs are nontrivial and they display substantial dispersions both across products and across city-pairs. At the product level, the average BW estimate varies widely across products ranging from 5.9% (*McDonald's Hamburgers*) to 28.2% (*Potatoes*), implying that within a band of 5.9% and 28.2% there are no forces in action to pull the relative prices back to the inaction band.[14] Such average statistics, however, provide only limited information on the degree of market friction as they mask a tremendous degree of heterogeneity across city-pairs within products. Indeed we notice a wide dispersion of BW within each product, with a greater cross-city pair dispersion for the products with a larger average BW. Take *Potatoes* for example, the city-pair BW is in the wide range between 6.1% and 54.9%. This indicates the potential role played by location-specific factors in explaining market segmentation. The large values of BW observed in many food-related items for which sales taxes are typically either exempt or very low implicitly implies a weak relevance of sales taxes to consumer market segmentation (e.g., Besley and

[13] We simply point out the main characteristics of eq.(1) here because a rigorous micro foundation of this equation can be found in a number of papers (e.g., Obstfeld and Taylor 1997, Imbs et al. 2003, O'Connell and Wei 2002, Sarno et al. 2004). While symmetric TAR models ($|\tau_L| = \tau_U$ and $\gamma^k = \beta^k$) has been popularly employed in the previous studies, our model here allows for different responses of relative prices to positive deviations from the band than to negative deviations because there seems no strong a priori reason to assume that. Though not reported here to conserve the space, we find qualitatively, though not quantitatively, similar results from the symmetric band-TAR model. Notice that the linear AR model is a nested special case of our band TAR model where $\tau_U^k = \tau_L^k = 0$ and $\gamma^k = \beta^k$.

[14] In comparison with the previous studies based on the symmetric TAR models (e.g., Obstfeld and Taylor 1997, O'Connell and Wei 2002), our bandwidth estimates appear to be somewhat larger. But the discrepancy largely arises from the difference in TAR models. The BW estimates from symmetric TAR model by Obstfeld and Taylor (1997) using the disaggregated price indices of some selected U.S. cities are around 1-6 percent, which correspond to 2-12 percent in the asymmetric TAR model. O'Connell and Wei (2002) report 5-12 percent symmetric BW for the goods that are not locally produced. In an international context, Sarno et al. (2004) find a wide sectoral variation of bandwidth, ranging from 1 percent for paper products to 20 percent for food, beverages and tobacco. The authors also find that bandwidth widely varies across countries for a given sector.

Rosen 1999).

To our surprise, BW is not necessarily larger for service products, which are conventionally labeled as non-tradables, compared to traded goods. In theory, prices in two markets should differ more for products that are less traded (e.g., services) where shocks to prices may persist longer, as often reflected by the substantially larger average price differentials for services. One might therefore expect to find larger BW's for non-traded services, and goods that have a larger proportion of non-traded inputs (Crucini et al., 2005). The average BW for service products like *Dry Cleaning* (8.2%) and *Movie* (7.0%), however, turns out to be far smaller than those for typical tradable goods such as *Lettuce* (24.6%), *Bread* (22.1%), and *Canned Peas* (20.7%). This outcome obviously poses a challenge to the popular view in the literature that a higher degree of market segmentation in service products that are typically produced locally and hence less tradable. On the other hand, our finding can be seen as consistent with the recent finding by Gervais and Jensen (2015) that many service industries have comparable trade costs to manufacturing industries. This also corroborates our original belief that transaction cost is not the single driving factor responsible for the segmentation of consumer markets.

The top panel of Figure 2 reinforces this point by plotting the empirical distribution of BW estimates for three sub-groups of product: perishables (P), non-perishables (N), and service (S). The top-left panel of Figure 2 shows little difference in the distribution of BW among the three product groups. In contrast to the conventional wisdom, the distribution of the market segmentation measure is not much different between service and the two product groups that are more tradable. This is probably because every product virtually contains some non-tradable component, or perhaps because markets for tradable products are connected through labor markets that are highly non-tradable. As displayed in the top-right panel of Figure 2, the conclusion remains same when the products are grouped based on the proximity of production to markets along the lines of O'Connell and Wei (2002): not locally produced, maybe locally produced, and locally produced. Since the distribution of 'locally produced' products are located to the left of that of 'not locally produced' products, the size of market segmentation is smaller for locally produced products that are typically services.

Our results also suggest that the average size of market segmentation is far smaller across cities than across products. As can be seen from the left-hand panel of Table 4, the cross-product average BW estimates exhibit quite a tight range between 13.9% (Lexington, KY) and 18.2% (Tacoma, WA). Interestingly, we notice that the extent of market segmentation in cities is seemingly related to their geographic location. To be more specific, the cities that are located along two coastlines and hence located farther away from the other cities, such as L.A., Tacoma and Philadelphia, tend to have a greater BW estimate, compared to the cities that are located in the middle of the continental U.S. (e.g., Lexington, KY). This implies that geographic location of cities may have a significant influence on the extent of market segmentation. To find concrete evidence to substantiate this claim, we plot the measures of market segmentation of each city (on the vertical axis) against the so-called remoteness measure (on the horizontal axis) in Figure 3 which captures an output weighted average distance vis-à-vis all other cities.[15] There is a clear positive association between remoteness and the metrics of market segmentation, indicating that cities which are more remote from others tend to have a larger size of market segmentation. In this sense, distance and income differentials between cities bear potential explanatory power on the dispersion of market segmentation across locations.

In addition, we find that the deviations that are outside the bands are relatively short lived. When price deviations exceed the upper or lower threshold bounds, prices are relatively quickly pushed back towards the band of inaction within less than a quarter of half-lives in most cases under study. The average half-life (HL) estimate is of the order of just one quarter in the vast majority of city-pair price differences, indicating that it takes only 3 months for the impact of the shock to decay by half once the LOP deviation of product prices exceeds the threshold levels. It is worth noting that compared to the HL estimates based on a linear AR model (right most columns of Table 3), intercity price differences disappear at a much faster speed outside the band.

3.2 Linear AR model and long-run average price differences (LAPD)

Another popular approach to drawing inference on market segmentation from the dynamic behavior of price differences is to estimate *long-term average price differentials* (LAPD) within the following linear autoregressive (AR) model framework (e.g., Goldberg and Verboven 2005),

$$\Delta q^k_{ij,t} = \kappa^k(1-\rho^k) - (1-\rho^k)q^k_{ij,t-1} + \sum_{j=1}^{m} \delta_j \Delta q^k_{ij,t-j} + \varepsilon^k_{ij,t}, \tag{2}$$

where $q^k_{ij,t}$ is the (log) price differential of product k between cities i and j at time t. The constant term $(\kappa^k(1-\rho^k))$ captures city-pair fixed effects that account for non-time dependent, city-pair specific

[15] Remoteness for city i from city j is calculated by $\sum_{k=1,k<>j}^{48} \frac{D_{ik}}{Y_k}$ where D_{ik} denotes the distance between cities i and k and Y_k represents the per capita income of city k. The cities on both coasts are among the more remote, while the cities in the central time zone are less remote. See Wolf (2000, p.556) for a further discussion on the remoteness measure.

price differences across locations. As noted by Goldberg and Verboven (2005), such fixed effects measured as percentages of price differences could be informative about transportation costs, markup differences or unobserved quality differences that vary by destination.[16] The speed of convergence is captured by the parameter ρ^k with a faster disappearance of price difference for a smaller value of ρ^k. The long-term, systematic price differentials between city-pair is then captured by κ, which is conceptually related to the size of market segmentation. When the price differentials reflect differences in observed costs, such as marginal costs and transport costs, one would expect market segmentation to lead to a deviation from harmonization of costs.

The right-hand panel of Table 3 presents the mean, median, and the 5^{th}- and 95^{th}-percentiles of the city-pair LAPD estimated from the linear AR model in eq.(2). The diagnostic statistics of the LAPD are qualitatively similar to those of the BW particularly in terms of considerable cross-product and within product variations in market segmentation. The LAPD estimates are in the range between 7.5% (*Toothpaste*) and 13.6% (*Dentist's Visit*), indicative of the presence of large and persistent intercity price differences in the long run. Long-run price differences of this magnitude seem hardly reconcilable with the common belief of market integration within national borders. Quantitatively, however, the LAPD estimates do not match closely with the BW estimates. Take *McDonald's Hamburgers* for example, the magnitude of market segmentation based on BW estimate is much smaller than those of other products, while that based on LAPD appears to be much larger compared to other products.

To further probe whether and how the two metrics of market segmentation have similar profiles, we plot in Figure 4 the average BW estimates against the average LAPD estimate by products (on the left) and by cities (on the right). It is evident from the plots that a clear positive association exists between the two metrics at the city level, while no such association is noticed at the product level, indicating that the two measures are in more agreement at the city level than at the product level. Since this indicates that the two measures of market segmentation may capture different aspect of market segmentation at the product level, comparing the results from the two metrics of market segmentation helps us gain further insight on the issue at hand.

[16] Interestingly, Goldberg and Verboven (2005) interpreted the constant term ($\kappa^k(1-\rho^k)$) as a measure of market segmentation by stating that "...in examining the absolute values...; large values of these city-pair specific effects would indicate market segmentation,..." (p.61).

4 Sources of market segmentation

The compelling evidence of consumer market segmentation in the U.S. leads to the natural question of what factors may account for it. In this section, we exploit the wide variation in observed market segmentation across cities and products to identify the main factors behind it. We look at both city pair specific and product specific explanatory factors. The main potential city pair factors include distance between cities, real income differences and relative population-size. The product specific factors are product types and proximity of production to markets. In the literature, these factors have been identified as important drivers of market segmentation.

4.1 Common factors behind market segmentation

Previous research and prior intuitions suggest that distance, differences in incomes and population may explain a large portion of the market segmentation observed in the data. To explore their relevance, we first estimate a common factor model which decomposes the variation in our market segmentation measures (BW and LAPD) into two components: one reflecting common component that is applicable to all products for each city-pair, and the other reflecting idiosyncratic component that is specific to each product. This decomposition allows us to identify the factors behind the market segmentation that are common to all products for each city-pair.

We consider the following prototypical factor representation[17],

$$\widehat{MS}_{ij}^{k} = a^k + \underbrace{\lambda_k' F_{ij}}_{C_{ij}} + e_{ij}^k, \qquad k = 1, ..., 45, \tag{3}$$

where $\widehat{MS}_{ij}^{k}$ denotes the two metrics of market segmentation for city-pair i and j in product k, a^k represents a product fixed effect, C_{ij} is a common component for city-pair i and j, and e_{ij}^k is an idiosyncratic component associated with idiosyncratic city-pair specific events or measurement error. Note that the common component (C_{ij}) is the product of the $r \times 1$ vector of common factors (F_{ij}) that captures the sources of variation in city-pair market segmentation common to all products, and the factor loading (λ_k) which captures the 'sensitivity' of market segmentation measure in product k to the common factor. Before estimation, the market segmentation measures are demeaned to remove individual fixed effects and standardized, i.e. divided by their sample standard deviation to

[17] A distinctive feature of our approach here is that the dependent variable is not observed but instead generated. Although the statistical properties of the estimators are unknown, we posit that the use of estimated regressand is inconsequential to the key conclusions of our analysis.

deal with cross sectional heteroskedasticity. There is one common factor in eq.(3), which was selected using a 'minimum rule' proposed by Greenaway-McGrevy et al. (2010).

Since we are interested in detecting the determinants of market segmentation here, we relate the estimated common factor ($\widehat{F_{ij}}$) to several potential sources of market segmentation. The basic idea of this exercise is that if those potential factors are indeed responsible for the segmentation between markets, they should be meaningfully (and positively) associated with the common factor of market segmentation. Figure 5 plots the estimated common factor of city-pair market segmentation ($\widehat{F_{ij}}$) against three candidate explanatory variables of market segmentation - distance (left panel), real income difference (middle panel), and relative city size (right panel). Recall that geographic distance between cities has traditionally been considered a reasonable proxy for transport costs (e.g., Anderson and van Wincoop 2004). Real income differences between cities are another potential source of market segmentation according to the Harrod-Balassa-Samuelson and pricing-to-market hypotheses. Alessandria and Kaboski (2011), Atkeson and Burstein (2008) and others suggest that much of the geographic variation in market segmentation explained by a vast large variations in wages, incomes and related markups across cities. Our city-level real per capita income data are constructed by deflating nominal income using the city-level price data of Carrillo et al. (2010). Relative city size, often measured by city-pair population differences, can also help explain the large cross-city dispersion in the magnitude of market segmentation especially through market competition and local costs (e.g., Desmet and Parente 2010). Larger cities, in the sense of more people or bigger markets, are likely to have lower markups through more competitions.

As can be seen from Figure 5, all three explanatory variables appear to be positively associated with the common factor estimates. The positive association implies that the forces which commonly affect the segmentation of markets across products are positively related to the three explanatory variables. To rephrase, markets that are farther apart or that have larger differences in real per capital income or population size are likely to be more segmented with larger values of BW and LAPD. Among the three candidate explanatory variables, distance stands out as it appears to be much more closely associated with the common factor. Our results here, while intuitive, are qualitative and hence further analysis is needed to quantify the effects of these candidate explanatory variables on market segmentation.

4.2 Regression analysis

In this section, we carry out regression analysis and quantify the effects of city characteristics (distance between city pairs, relative city incomes and relative city sizes / populations), and product characteristics (product type and distance to market place) on market segmentation. Since trade costs encompass local distribution costs (e.g., Inanc and Zachariadis 2012), one may well expect individual products with different characteristics to have different levels of market segmentation. Motivated by this, we classify our 45 products into three types - perishables(P), non-perishables(NP) and services(S). Our prior is market segmentation will be lower the more tradable the product is. Our second classification follows O'Connell and Wei (2002) who classify the products into three categories based on the proximity of production to the marketplace: (A) not locally-produced goods; (B) maybe locally-produced goods; and (C) always locally-produced goods. Locally-produced goods are harder to transport, and thus are likely more affected by local factors such as distribution costs and markups. In consequence, our prior is that markets for locally produced products are more segmented than markets for products that are not locally produced.

To investigate the quantitative effect of these city pair and product variables, we ran the following pooling regressions where the two metrics of market segmentation are regressed against a set of aforementioned explanatory variables. Here, we consider two model specifications of regression depending on whether we treat distance per se or its decomposition into transport and other cost components.[18]

$$\widehat{MS}_{ij}^{k} = \rho \log(DIST_{ij}) + X\beta + \varepsilon_{ij}, \qquad \text{(Specification 1)} \tag{4}$$

$$\widehat{MS}_{ij}^{k} = \alpha_1 TC_{ij} + \alpha_2 NTC_{ij} + X\beta + \varepsilon_{ij}, \qquad \text{(Specification 2)} \tag{5}$$

where $\widehat{MS}_{ij}^{k}$ represents the BW or LAPD metric of market segmentation between cities i and j for product k and $DIST_{ij}$ denotes the distance between cities i and j measured by the greater circle formula based on the city's latitude and longitude data.[19] It is important to note that $DIST_{ij}$

[18] Since estimated values are used as dependent variable, our regression is subject to the issue of so-called estimated dependent variables (EDV) problem and the estimator could be heteroskedastic. We address this issue by using the heteroskedasticity-robust standard errors as suggested by Lewis and Linzer (2005). Another issue with regard to the dependent variable is that BW estimates in Figure 2 appear to be skewed to the right. Using quantile regression analysis whose results are not reported here to conserve space, we confirm that the skewed nature of dependent variable does not alter our main conclusions.

[19] The greater-circle distance or orthodromic distance is the shortest distance between any two points measured along a path on the surface of the sphere. Minimum driving distance seems more appropriate for the U.S. cities where the majority of shipments are transported either by road or by a road-rail combination (e.g., Wolf 2000). Using both

varies across city-pairs but not across products. X denotes a set of other explanatory variables, $X = \{RINCOME_{ij}, POPULATION_{ij}, SAMESTATE_{ij}, D_k^P, D_i^C, D_j^C\}$, where '$RINCOME$', and '$POPULATION$' respectively denote city-pair differences in real per capita income and population computed by $[max(z_i, z_j) - min(z_i, z_j)]/max(z_i, z_j)$ in which z_h denotes the corresponding variable for city h.

The variable '$RINCOME$' is the log difference in real income per capita between cities i and j and captures the local (distribution) cost component as suggested by Anderson and van Wincoop (2004). It also captures cross-city differences in the wage component of local distribution costs such that higher wages in the high income cities may push up the cost of all products, including goods due to the labor input into distribution. The mark-up is also likely to be higher in the high income cities if sellers exercise pricing-to-market practices. The difference in population size ('$POPULATION$') is meant to capture the effect of relative market size. As discussed earlier, the coefficients for both '$RINCOME$', and '$POPULATION$' are therefore expected to have a positive effect on the size of market segmentation.

'$SAMESTATE$' represents an intra-state dummy variable which takes on the value of one if two cities are in the same state and zero otherwise. As an inverse measure of state border effect, it controls for state-specific characteristics like policy environment and state-tax. Consequently, it is expected to enter with a negative sign because cities in the same state are likely to have similar price levels, due to more homogeneous economic environments (e.g., industrial structure) and tax schemes. D_k^P denotes product-specific dummies. City fixed effects (D_h^C) capture the effect of all the differences that are invariant to a city-pair other than distance and differences in real income and population, such as the influence of the local retailers' pricing strategies. ε_{ij} is the error term that could be cross-sectionally correlated and possibly heteroskedastic.

In the second model specification, we follow Choi and Choi (2014) and break down the distance effect into the part attributable to transport costs (TC), and the other part that is orthogonal to TC and hence dubbed as non-transport costs (NTC),[20] by utilizing the data on inter-spatial trade cost constructed by Allen and Arkolakis (forthcoming). Since NTC may contain the information on local distribution costs and mark-up rates that are known to constitute a large component of final

measures of distance, however, Engel and Rogers (1996) conclude that the results are unaffected by the choice of distance measure.

[20] Whereas the conventional literature has interpreted distance effect as solely reflecting transport costs, distance may induce price wedges between locations via additional channels to transport costs in view of the growing evidence that other factors may also operate on the geographic distance (see Choi and Choi 2014 and the references therein).

consumer prices, the distinction between the two channels provides additional insights into market segmentation.[21]

Table 5 presents the regression results for both model specifications. The top panel sets out the results for all 45 products. All of the explanatory variables are highly significant and have the expected signs. That is, markets are more segmented for the city-pairs that are farther apart or that have larger differences in real incomes and population. Looking at their quantitative effect, we find that a ten percent increase in the distance between two cities *ceteris paribus* increases the city-pair market segmentation by around 0.06 percentage point (BW) and 0.19 percentage point (LAPD). Similarly, the effect of a ten percent increase in real income difference ('$RINCOME$') and relative population ('$POPULATION$') between two cities is to increase the size of BW-based market segmentation by 11 percent and 3.5 percent, respectively. The finding that a larger difference in population size is associated with greater market segmentation suggests a potential role for markup differences across cities in explaining market segmentation. Alternatively, scale economies in distribution related to market size might also be behind this finding. The coefficient for '$SAMESTATE$' dummy variable takes an anticipated negative sign, indicating that two cities in the same state are likely to have a smaller size of market segmentation. The coefficient on the same state dummy tells us that, *ceteris paribus*, on average the size of market segmentation is 1.3-1.6 percent lower for the city-pairs within the same state. It is reassuring to note that the BW and LAPD results are very consistent in terms of the signs and significance of the explanatory variables. In both cases, distance is the most important explanatory variable for market segmentation.

In order to understand the role of product characteristics, the middle panel of Table 5 reports the regression results when separate regressions are run the for the three categories: perishable (P), non-perishable goods (NP) and services (S). The significance and the size of the distance and other effects differ markedly by product type. For example, consider the marginal effect of distance on BW in the "specification 1" columns. It is 0.012 for perishable products and approximately zero for services. This finding squares well with the conventional wisdom that perishable products have higher arbitrage costs, since they are more easily spoiled within a short period of time, and hence markets are more segmented by physical proximity. By contrast, consumers of services such as a routine visit to a doctor or a haircut are hardly likely to arbitrage inter city price differentials away.

[21] Note that the regressor NTC is a residual and is subject to the so-called generated regressor problem (e.g., Pagan 1984) that invalidates OLS-based standard errors. Since we don't have lags in our regression analysis, there is no generated regressor problem in our case.

For the non-perishable products, distance is highly significant but has a smaller effect on BW than it does for perishables. Notice that the other explanatory variables, both '$POPULATION$' and '$RINCOME$', are significant only in the perishable group. Although high-income cities are known to have higher prices, our results surprisingly suggest that the effect of real income differences on market segmentation is not significant for other than perishable goods. The state border effect is significant for both perishable and non-perishable goods, with the estimated border effects being 2.0 and 1.6 percentage points respectively.

Qualitatively similar results are obtained from the second model specification where the distance effect is broken down into TC and NTC components. TC is significant not only for tradable goods but also for non-traded service, suggesting that distance contains more information than transport costs as emphasized by Choi and Choi (2014). This result may derive, in part, from the fact that service products contain a substantial amount of nontraded local inputs. These local input costs are likely more similar in nearby locations due to the geographically integrated nature of many labor markets (e.g., Engel et al. 2003). Moreover, as noted by Redding and Turner (2014), other than the reduction in transportation costs, geographic proximity has an advantage of agglomeration effect including knowledge spillovers and idea flows. It is often claimed that labor markets are still local even in the era of the internet.

A similar systematic pattern of results is noted in the bottom panel of Table 5, where products are grouped on the basis of the proximity of production to market. The regression results largely conform to our priors. Most of the explanatory variables enter significantly with the correct signs. Distance has the greatest effect on market segmentation in the product group that is not locally produced, while it has the smallest effect in the group of locally produced products. This finding accords well with our initial intuition that locally produced products are subject to local factors and hence transportation costs should matter little.

4.3 Stability of market segmentation over time

Our estimates of market segmentation implicitly assume that the dynamics of intercity price differences and their long run levels or bands do not vary substantially over the entire sample period. In the band TAR model, for example, BW is estimated under the assumption that thresholds are fixed for the sample period. Of course, this assumption may be fragile if rapid developments in transportation, logistics and information technologies have reduced the width of inaction band. In fact, it is well established in the literature that there is a secular decline in transportation costs for goods (e.g., Redding and Turner 2014). It is therefore important to investigate whether or not the estimates of market segmentation do vary over time. Ideally we would like to estimate time-varying parameter band-TAR models, but the estimation cost of time-varying parameter band-TAR models, with an iterative grid search over the thresholds, is excessive. This cost is particularly high in our case due to the large number of city-pairs, namely for more than 50,000 city-pairs under study. Alternatively, we can look for changes in the densities of the intercity price differentials over time and examine the stability of the LAPD estimates using rolling regression analysis.

We first look at the stability of the distribution of the intercity price differentials over time. A notable shift in the distribution of price differences over time may indicate a time-varying feature of market segmentation. Figure 1 shows the evolution of empirical densities of annualized intercity price differences over the sample period. With the notable exception of *Frozen Corns* (Item 24), the other 44 densities look quite stable over the 25 years, lending little credence to the argument of time-varying market segmentation.

A similar story is told from Figure 6 which displays the rolling regression estimates of LAPD over the sample period. The rolling regression estimates of LAPD were generated using a twelve year moving window to estimate the linear AR model in eq.(2). Specifically the estimates were obtained using data from t to $t + 48$. In each panel of Figure 6, the solid line denotes the time t median estimate of LAPD across the 1,128 city-pairs. The two dashed lines are the corresponding 25^{th} and 75^{th} percentiles. We notice a mild upward trend in some products such as *Frozen Corn* and *Cornflakes*, indicative of an increase in market segmentation over time. By contrast, a moderate downward trend is noted in some other products like *Movies* where market segmentation appears to have declined a little over time, possibly owing to the improvements in transport and communication technologies and the associated reduction in transport costs. Other than these three products, the rolling regression LAPD estimates look stable over time, without any drastic shifts or discrete variations. This evidence does not refute our use of time-invarying measures of market segmentation.

5 Concluding remarks

We quantified the magnitude and persistence of market segmentation in U.S. consumer market, and explored the underlying factors generating this segmentation, using a quarterly panel of retail prices for 45 products in 48 U.S. cities over the twenty five year period 1985 to 2009. The extent of market segmentation is estimated using both autoregressive and band threshold autoregressive models. In the band TAR model, the price differential reverts nonlinearly towards a long run band. We found significant, persistent level of intercity market segmentation in the U.S. consumer markets, even though relative price shocks are generally short lived. Market segmentation varies widely across both cities and products. Contrary to the common belief, market segmentation is not necessarily larger for non-tradable services compared to tradable goods. In fact, we find little difference in the size distributions of market segmentation between tradable and non-tradable products.

We utilized regression analyses to identify the potential drivers of market segmentation by relating the level of market segmentation to location-specific and product-specific characteristics - distance between cities, relative city sizes, relative incomes, type of product and proximity to marketplace. Distance turns out to be most salient factor, although it captures other factors than transport costs since the level of market segmentation in services is also increasing in distance. The effect of distance, however, varies by product characteristic. Greater distance generates significantly higher levels of market segmentation for perishable products and products that are not locally produced. Relative income effects appear to be small. When we decompose the distance effect into the part attributable to transport cost and the remaining part due to non-transport cost, we find that markets for non-traded services are mainly segmented by the latter while market segmentations for traded goods are driven by both components.

Our U.S. results have implications for the level of market segmentation in currency unions, such as the Eurozone (EZ). Despite the long term policy of promoting greater product and labor market competition and integration, it is widely agreed that the integration of a market for goods and services in the EZ has yet been realized. Our finding that distance accounts for a lion's share of the intercity consumer price differentials in the U.S. is somewhat encouraging to the policymakers in the EZ in view of the geographical proximity of major cities in the area. With that said, it is important to note that language, cultural and other barriers to the flow of factors between cities in the EZ are far greater than in the U.S. Differences in income and expenditure taxes are also greater. In addition, without fiscal union, country specific negative economic shocks in the EZ are likely to be more important than region specific shocks in the U.S. Given these factors, the large cross-country dispersion in consumer prices in the EZ is unlikely to change dramatically in the next few decades.

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Appendix: Data Description

Table A.1: Product Descriptions

Number	Item	Class1	Class2	Descriptions
1	Steak	P	B	Pound, USDA Choice
2	Ground beef	P	B	Pound, lowest price
3	Whole chicken	P	B	Pound, whole fryer
4	Milk	P	B	1/2 gal. carton
5	Eggs	P	B	One Dozen, Grade A, Large
6	Margarine	P	B	One Pound, Blue Bonnet or Parkay
7	Cheese	P	A	Parmesan, grated 8 oz. canister, Kraft
8	Potatoes	P	B	10 lbs. white or red
9	Bananas	P	A	One pound
10	Lettuce	P	B	Head, approximately 1.25 pounds
11	Bread	P	B	24 oz loaf
12	McDonald's	P	C	McDonald's Quarter-Pounder with Cheese
13	Pizza	P	C	12"-13" (85.1-94.3), 11"-12" (94.4-09.4) thin crust cheese pizza, Pizza Hut or Pizza Inn from 1990Q1 to 1994Q3
14	Fried chicken	P	C	Thigh and Drumstick, KFC or Church's where available
15	Canned tuna	N	A	Starkist or Chicken of the Sea; 6.5 oz.(85.1-91.3),6.125 oz.(91.4-95.3), 6-6.125 oz.(95.3-99.4), 6.0 oz. (00.1-09.4)
16	Coffee	N	A	Can, Maxwell House, Hills Brothers, or Folgers; 1 lb. (85.1-88.3); 13 oz. (88.4-99.4); 11.5 oz. (00.1-09.4)
17	Sugar	N	B	Cane or beet; 5 lbs. (85.1-92.3); 4 lbs. (92.4-09.4)
18	Corn flakes	N	A	18 oz, Kellog's or Post Toasties
19	Canned peas	N	A	Can, Del Monte or Green Giant; 17 oz can, 15-17 oz. (85.1-85.4), 17 oz. (86.1-91.4), 15-15.25 oz. (92.1-09.4)
20	Canned peaches	N	A	1/2 can approx. 29 oz.; Hunt's, Del Monte, or Libby's or Lady Alberta
21	Tissue	N	A	175-count box (85.1-02.3), 200-count box (02.4-09.4); Kleenex brand
22	Detergent	N	A	42 oz, Tide, Bold, or Cheer (85.1-96.3); 50 oz. (96.4-00.4), 60 oz (01.1-02.3), 75 oz (02.4-09.4), Cascade dishwashing powder
23	Shortening	N	A	3 lbs. can, all-vegetable, Crisco brand
24	Frozen corn	N	A	10 oz. (85.1-95.3), 16 oz. (95.4-09.4); Whole Kernel
25	Soft drink	N	A	2 liter Coca Cola
26	Gas	N	A	One gallon regular unleaded, national brand, including all taxes
27	Toothpaste	N	A	6 to 7 oz. tube (85.1-06.2), 6 oz-6.4oz tube (06.3-09.4); Crest, or Colgate
28	Man's shirt	N	A	Arrow, Enro, Van Huesen, or JC Penny's Stafford, White, cotton/polyester blend (at least 55% cotton) long sleeves (85.1-94.3); 100% cotton pinpoint Oxford, Long sleeves (94.4-99.4)Cotton/Polyester, pinpoint weave, long sleeves (00.1-09.4)
29	Tennis balls	N	A	Can of three extra duty, yellow, Wilson or Penn Brand
30	Beer	N	A	6-pack, 12 oz containers, excluding deposit; Budweiser or Miller Lite, (85.1-99.4), Heineken's (00.1-09.4)
31	Wine	N	A	1.5-liter bottle; Paul Masson Chablis (85.1-90.3) Gallo sauvignon blanc (90.4-91.3), Gallo chablis blanc (91.4-97.3) Livingston Cellars or Gallo chablis blanc (97.1-00.1) Livingston Cellars or Gallo chablis or Chenin blanc (00.2-09.4)
32	Apartment rent	S	C	Two-Bedroom, unfurnished, excluding all utilities except water, 1.2 or 2 baths, approx. 950 sqft
33	Home price	S	C	1,800 sqft, new house, 8,000 sqft lot, (85.1-99.4); 2,400 sqft, new house, 8,000 sqft lot, 4 bedrooms, 2 baths (00.1-09.4)
34	Monthly payment	S	C	Principal and Interest, assuming 25% down payment
35	Telephone	S	C	Private residential line, basic monthly rate, fees and taxes
36	Auto maintenance	S	C	average price to balance one front wheel (85.1-88.3); average price to computer or spin balance one front wheel (88.4-09.4)
37	Doctor visit	S	C	General practitioner's routine examination of established patient
38	Dentist visit	S	C	Adult teeth cleaning and periodic oral examination (85.1-04.4); Adult teeth cleaning (05.1-09.1)
39	Man's haircut	S	C	Man's barber shop haircut, no styling
40	Beauty salon	S	C	Woman's shampoo, trim, and blow dry
41	Dry cleaning	S	C	Man's two-piece suit
42	Appliance repair	S	C	Home service call, washing machine, excluding parts
43	Newspaper	S	C	Daily and Sunday home delivery, large-city newspaper, monthly rate
44	Movie	S	C	First-run, indoor, evening, no discount
45	Bowling	S	C	Price per line, evening rate (85.1-98.2); Saturday evening non-league rate (98.3-09.4)

Notes: The 'Class1' denotes the type of product classification that refers to non-perishable goods (N), perishable goods (P) and services (S), while 'Class2' denotes the second product classification based on the proximity of production to the market place in which categories A, B and C refer to not locally produced, maybe locally produced and locally produced goods and services respectively. The two classifications are related as follows.

	P	N	S	Total
A	2	16	0	18
B	9	1	0	10
C	3	0	14	17
Total	14	17	14	45

Table A.2: Data description of explantary variables

Variable	Description	Source
Distance	The great circle distance computed by using the latitude and longitude of each city	The American Practical Navigator (relevant website)
Income	Average personal income of the U.S. Metropolitan area during 1976-2009	BEA website
Population	Average populations of the U.S. Metropolitan area during 1976-2009	Census Bureau website
Population density	Average populations of the U.S. Metropolitan area per square miles during 1980-2000	Census Bureau website
Price	Average city-level CPI of metropolitan area in the U.S. during 1982-2008	Carrillo et al. (2010)

Table A.3: City-level characteristics (period average)

City code	City name	State	Income (dollars)	Population (thousands)	Pop. Density (per sq. miles)	CPI	Remoteness
1	ABILENE	TX	16,938	140	1,017.6	0.814	0.151
2	AMARILLO	TX	17,905	218	1,782.1	0.805	0.151
3	ATLANTA	GA	21,560	4,143	3,125.7	0.925	0.138
4	CEDAR RAPIDS	IA	20,238	212	1,793.8	0.826	0.080
5	CHARLOTTE	NC	21,190	1,402	1,722.9	0.865	0.220
6	CHATTANOOGA	TN	18,196	470	1,177.1	0.844	0.083
7	CLEVELAND	OH	16,100	2,173	6,693.5	0.903	0.224
8	COLORADO SPRINGS	CO	19,419	519	1,537.0	0.864	0.240
9	COLUMBIA	MO	18,078	139	1,355.0	0.830	0.241
10	COLUMBIA	SC	18,213	589	854.5	0.817	0.005
11	DALLAS	TX	22,536	3,423	3,017.5	0.900	0.089
12	DENVER	CO	24,482	2,082	3,293.0	0.933	0.256
13	DOVER	DE	16,840	131	1,239.7	0.901	0.426
14	FAYETTEVILLE	AR	16,449	125	1,050.7	0.768	0.003
15	GLENS FALLS	NY	16,747	124	3,940.3	0.911	0.574
16	GREENVILLE	NC	16,319	142	1,857.2	0.811	0.363
17	HOUSTON	TX	22,862	4,703	2,979.8	0.870	0.193
18	HUNTSVILLE	AL	19,450	347	882.1	0.832	0.064
19	JONESBORO	AR	14,821	93	559.1	0.749	0.000
20	JOPLIN	MO	15,555	154	1,331.4	0.760	0.003
21	KNOXVILLE	TN	18,463	646	1,849.0	0.787	0.106
22	LEXINGTON	KY	20,257	435	808.4	0.856	0.087
23	LOS ANGELES	CA	22,628	9,406	7,212.1	0.797	0.848
24	LOUISVILLE	KY	19,914	1,094	4,424.1	1.039	0.059
25	LUBBOCK	TX	16,951	245	1,626.3	1.005	0.178
26	MEMPHIS	TN	19,617	1,157	2,275.3	0.859	0.014
27	MOBILE	AL	15,404	456	1,684.0	0.904	0.179
28	MONTGOMERY	AL	18,062	334	1,216.3	0.793	0.139
29	ODESSA	TX	16,271	180	2,451.7	0.813	0.240
30	OKLAHOMA CITY	OK	19,120	1,080	744.0	0.829	0.050
31	OMAHA	NE	21,435	738	2,995.3	0.830	0.085
32	PHILADELPHIA	PA	23,417	4,435	11,822.6	0.979	0.447
33	PHOENIX	AZ	19,604	3,218	2,172.0	0.874	0.565
34	PORTLAND	OR	21,454	1,889	3,315.6	0.905	1.057
35	RALEIGH	NC	21,780	967	1,857.0	0.883	0.302
36	RENO-SPARKS	NV	24,832	337	2,062.3	0.956	0.874
37	RIVERSIDE	CA	17,365	3,345	2,784.1	0.978	0.807
38	SALT LAKE CITY	UT	18,863	111	1,542.3	0.924	0.523
39	SAN ANTONIO	TX	17,870	1,661	2,344.0	0.812	0.245
40	SOUTHBEND	IN	18,663	1,117	2,783.8	0.798	0.120
41	SPRINGFIELD	IL	20,742	2,796	1,956.3	0.807	0.027
42	ST. CLOUD	MN	16,813	169	1,663.2	0.859	0.236
43	ST. LOUIS	MO	21,488	202	6,447.4	0.848	0.004
44	SYRACUSE	NY	19,071	696	6,393.9	0.873	0.460
45	TACOMA	WA	24,715	695	3,519.2	0.881	1.082
46	TUCSON	AZ	17,189	838	2,093.5	0.855	0.546
47	WACO	TX	16,279	210	1,261.2	0.810	0.134
48	YORK	PA	20,124	383	8,184.2	0.868	0.376

Note: 'income' represents the average nominal per capita income for the period of 1985-2009 and 'population' is the average population during 1980-2009. 'Pop. density' is the average population per square miles during 1980-2000. These variables are downloaded from the website of Census Bureau in BEA, and the city-level CPI data are borrowed from Carrillo et al. (2010) who created the panel of annual price indices entitled 'CEOPricesPanel02' that cover the period 1982 through 2008 for most metropolitan areas in the United States. 'Remoteness' for city i is calculated by $\sum_{k=1,k<>j}^{48} \frac{D_{ik}}{Y_k}$ where D_{ik} denotes the distance between cities i and k and Y_k represents the per capita income of city k.

Table 1: Summary statistics of intercity price differentials, 1985-2009

	Average price gaps			Volatility
item	mean	median	[10%,90%]	(s.d.)
1	0.134	0.128	[0.090, 0.187]	0.098
2	0.178	0.169	[0.125, 0.243]	0.130
3	0.193	0.177	[0.119, 0.294]	0.130
4	0.141	0.133	[0.088, 0.200]	0.095
5	0.188	0.142	[0.100, 0.324]	0.127
6	0.203	0.184	[0.130, 0.297]	0.140
7	0.116	0.109	[0.062, 0.183]	0.083
8	0.240	0.225	[0.159, 0.340]	0.166
9	0.175	0.160	[0.118, 0.257]	0.127
10	0.188	0.184	[0.132, 0.246]	0.143
11	0.221	0.201	[0.132, 0.337]	0.151
12	0.060	0.058	[0.039, 0.085]	0.056
13	0.092	0.084	[0.054, 0.142]	0.068
14	0.129	0.119	[0.081, 0.193]	0.088
15	0.167	0.159	[0.103, 0.235]	0.121
16	0.143	0.125	[0.083, 0.235]	0.097
17	0.121	0.114	[0.076, 0.176]	0.092
18	0.160	0.153	[0.108, 0.224]	0.119
19	0.157	0.144	[0.108, 0.226]	0.113
20	0.109	0.100	[0.068, 0.167]	0.083
21	0.116	0.107	[0.080, 0.161]	0.088
22	0.130	0.127	[0.090, 0.174]	0.095
23	0.120	0.114	[0.072, 0.175]	0.080
24	0.151	0.143	[0.107, 0.208]	0.123
25	0.153	0.141	[0.107, 0.221]	0.111
26	0.073	0.065	[0.045, 0.116]	0.054
27	0.144	0.135	[0.099, 0.200]	0.106
28	0.153	0.147	[0.113, 0.205]	0.119
29	0.158	0.149	[0.104, 0.220]	0.113
30	0.092	0.080	[0.054, 0.159]	0.064
31	0.165	0.148	[0.100, 0.254]	0.106
32	0.208	0.166	[0.081, 0.377]	0.096
33	0.188	0.140	[0.076, 0.366]	0.100
34	0.188	0.140	[0.077, 0.366]	0.102
35	0.217	0.196	[0.103, 0.358]	0.121
36	0.158	0.135	[0.087, 0.261]	0.098
37	0.162	0.152	[0.102, 0.234]	0.108
38	0.193	0.167	[0.102, 0.313]	0.113
39	0.161	0.144	[0.092, 0.258]	0.102
40	0.213	0.193	[0.120, 0.335]	0.131
41	0.155	0.136	[0.073, 0.268]	0.084
42	0.169	0.146	[0.099, 0.269]	0.111
43	0.257	0.235	[0.116, 0.442]	0.133
44	0.113	0.092	[0.053, 0.207]	0.079
45	0.186	0.169	[0.101, 0.301]	0.118

Note: Entries for the summary statistics represent mean, minimum, maximum, and volatility measures of period-average absolute price difference, $\frac{1}{T}\sum_{t=1}^{T}|\ln P_{it}^{h} - \ln P_{jt}^{h}|$, where $\ln P_{it}^{h} - \ln P_{jt}^{h}$ measures the percentage difference between the price of product h in cities i and j at time t.

Table 2: Results of unit-root test and linearity test

	Unit-root tests		Linearity tests		
item	ADF	DF-GLS	Tsay	LM	Hansen
1	0.568	0.620	0.280	0.263	0.256
2	0.682	0.722	0.317	0.341	0.285
3	0.598	0.592	0.286	0.275	0.243
4	0.345	0.486	0.317	0.377	0.266
5	0.605	0.621	0.306	0.340	0.274
6	0.569	0.644	0.289	0.324	0.269
7	0.365	0.475	0.323	0.359	0.263
8	0.670	0.613	0.262	0.269	0.249
9	0.631	0.675	0.332	0.349	0.287
10	0.581	0.658	0.361	0.364	0.271
11	0.505	0.519	0.322	0.364	0.273
12	0.586	0.602	0.570	0.645	0.461
13	0.638	0.586	0.439	0.562	0.343
14	0.574	0.601	0.471	0.530	0.337
15	0.591	0.664	0.334	0.373	0.266
16	0.596	0.656	0.329	0.360	0.282
17	0.696	0.767	0.289	0.305	0.242
18	0.450	0.606	0.319	0.351	0.287
19	0.549	0.638	0.279	0.302	0.241
20	0.500	0.534	0.429	0.505	0.341
21	0.547	0.678	0.391	0.377	0.310
22	0.598	0.624	0.315	0.324	0.261
23	0.463	0.556	0.433	0.474	0.395
24	0.458	0.536	0.316	0.323	0.269
25	0.611	0.569	0.257	0.250	0.251
26	0.661	0.735	0.266	0.297	0.244
27	0.525	0.532	0.319	0.349	0.271
28	0.595	0.620	0.262	0.293	0.240
29	0.605	0.659	0.353	0.360	0.320
30	0.580	0.589	0.449	0.494	0.349
31	0.646	0.664	0.408	0.414	0.387
32	0.354	0.425	0.345	0.328	0.295
33	0.369	0.414	0.362	0.391	0.302
34	0.426	0.456	0.319	0.361	0.255
35	0.392	0.365	0.563	0.694	0.424
36	0.546	0.530	0.339	0.404	0.284
37	0.472	0.511	0.436	0.525	0.326
38	0.507	0.537	0.458	0.514	0.355
39	0.546	0.509	0.576	0.607	0.429
40	0.478	0.548	0.484	0.522	0.396
41	0.468	0.431	0.457	0.598	0.402
42	0.517	0.559	0.403	0.445	0.340
43	0.384	0.402	0.720	0.802	0.698
44	0.546	0.456	0.626	0.693	0.605
45	0.469	0.452	0.513	0.549	0.401
Average	0.523	0.557	0.383	0.421	0.323

Note: Entries in the unit-root tests represent frequencies of rejections of unit-root null hypothesis at the ten percent significance level, i.e. the portion of 1,128 city-pair price differences. Entries in the linearity tests represent rejection frequencies for bootstrapped p-values at the 5% significance level of three linearity tests, Tsay test, the LM test developed by Dahl and Gonzalez-Rivera (2003), the Hansen test, i.e. the portion of city-level relative prices out of 1,275 series in which the null hypothesis of linearity is rejected at 5% on the basis of 2,000 replications.

Table 3: Measures of market segmentation

Item	Nonlinear TAR model					Linear AR model				
	BW			Half-life		LAPD			Half-life	
	mean	median	[5%,95%]	mean	[5%,95%]	mean	median	[5%,95%]	mean	[5%,95%]
1	0.174	0.189	[0.035, 0.350]	1.03	[1,1]	0.107	0.091	[0.006, 0.320]	1.28	[0.5, 3.8]
2	0.230	0.249	[0.047, 0.477]	1.07	[1,2]	0.120	0.104	[0.010, 0.348]	1.33	[0.6, 3.6]
3	0.216	0.235	[0.046, 0.422]	1.06	[1,1]	0.099	0.078	[0.005, 0.318]	1.38	[0.6, 3.8]
4	0.122	0.107	[0.033, 0.283]	1.48	[1,3]	0.100	0.089	[0.010, 0.271]	2.95	[1.3, 9.3]
5	0.183	0.194	[0.037, 0.414]	1.06	[1,1]	0.091	0.080	[0.009, 0.249]	1.13	[0.5, 3.1]
6	0.218	0.216	[0.048, 0.469]	1.20	[1,2]	0.103	0.088	[0.008, 0.284]	1.77	[0.8, 5.6]
7	0.107	0.099	[0.025, 0.257]	1.32	[1,3]	0.114	0.096	[0.009, 0.328]	2.61	[1.1, 13.9]
8	0.282	0.315	[0.061, 0.549]	1.02	[1,1]	0.097	0.086	[0.007, 0.269]	1.09	[0.5, 2.8]
9	0.198	0.195	[0.041, 0.436]	1.05	[1,1]	0.110	0.092	[0.008, 0.314]	1.35	[0.6, 3.5]
10	0.246	0.269	[0.051, 0.500]	1.02	[1,1]	0.113	0.099	[0.011, 0.325]	1.13	[0.4, 3.6]
11	0.221	0.214	[0.049, 0.485]	1.09	[1,2]	0.131	0.104	[0.010, 0.451]	1.86	[0.8, 6.6]
12	0.059	0.053	[0.012, 0.140]	1.61	[1,3]	0.131	0.106	[0.009, 0.450]	1.72	[0.8, 5.1]
13	0.080	0.063	[0.014, 0.223]	1.75	[1,3]	0.111	0.074	[0.007, 0.421]	2.44	[1.4, 5.8]
14	0.107	0.095	[0.023, 0.253]	1.36	[1,3]	0.087	0.070	[0.006, 0.289]	1.90	[1.0, 5.2]
15	0.170	0.139	[0.039, 0.409]	1.11	[1,2]	0.085	0.068	[0.006, 0.260]	1.61	[0.8, 4.3]
16	0.145	0.146	[0.034, 0.311]	1.12	[1,2]	0.112	0.090	[0.006, 0.334]	1.73	[0.8, 5.2]
17	0.160	0.165	[0.032, 0.328]	1.10	[1,2]	0.123	0.092	[0.009, 0.376]	1.54	[0.8, 3.6]
18	0.199	0.200	[0.045, 0.430]	1.20	[1,2]	0.105	0.088	[0.008, 0.294]	2.29	[1.0, 6.6]
19	0.207	0.227	[0.047, 0.377]	1.06	[1,1]	0.115	0.098	[0.008, 0.317]	1.58	[0.8, 4.5]
20	0.113	0.109	[0.026, 0.245]	1.43	[1,3]	0.117	0.096	[0.007, 0.355]	2.17	[0.9, 10.6]
21	0.143	0.155	[0.032, 0.295]	1.11	[1,2]	0.091	0.066	[0.007, 0.295]	1.65	[0.8, 4.7]
22	0.158	0.167	[0.035, 0.323]	1.15	[1,2]	0.084	0.073	[0.006, 0.251]	1.81	[0.9, 5.0]
23	0.089	0.072	[0.026, 0.221]	1.74	[1,4]	0.104	0.089	[0.010, 0.293]	3.04	[1.6, 7.2]
24	0.202	0.209	[0.042, 0.421]	1.18	[1,2]	0.095	0.078	[0.007, 0.276]	2.04	[0.9, 10.2]
25	0.199	0.215	[0.042, 0.390]	1.07	[1,1]	0.080	0.066	[0.005, 0.240]	1.37	[0.6, 4.0]
26	0.095	0.102	[0.018, 0.186]	1.01	[1,1]	0.117	0.096	[0.008, 0.380]	1.05	[0.5, 2.7]
27	0.167	0.179	[0.036, 0.340]	1.20	[1,2]	0.075	0.057	[0.005, 0.269]	1.85	[0.9, 6.0]
28	0.203	0.215	[0.046, 0.429]	1.17	[1,2]	0.100	0.086	[0.008, 0.287]	1.71	[0.9, 5.9]
29	0.167	0.141	[0.035, 0.396]	1.40	[1,3]	0.112	0.093	[0.008, 0.341]	2.14	[1.1, 5.0]
30	0.084	0.076	[0.020, 0.192]	1.39	[1,3]	0.109	0.088	[0.006, 0.364]	2.20	[1.1, 5.6]
31	0.155	0.155	[0.035, 0.324]	1.17	[1,2]	0.125	0.090	[0.006, 0.483]	1.71	[0.9, 4.5]
32	0.073	0.063	[0.023, 0.168]	3.69	[1,9]	0.085	0.070	[0.005, 0.272]	5.36	[2.8, 16.1]
33	0.081	0.071	[0.026, 0.194]	3.57	[1,7]	0.091	0.080	[0.007, 0.270]	5.01	[2.8, 12.9]
34	0.086	0.074	[0.027, 0.199]	3.22	[1,6]	0.089	0.078	[0.007, 0.249]	4.71	[2.6, 12.2]
35	0.117	0.102	[0.022, 0.297]	3.00	[1,7]	0.097	0.080	[0.005, 0.314]	4.34	[2.2, 16.3]
36	0.128	0.117	[0.029, 0.298]	1.35	[1,3]	0.105	0.085	[0.009, 0.328]	2.27	[1.1, 7.8]
37	0.128	0.108	[0.034, 0.297]	1.96	[1,4]	0.120	0.093	[0.007, 0.472]	3.14	[1.5, 11.1]
38	0.126	0.103	[0.033, 0.326]	1.84	[1,4]	0.136	0.113	[0.008, 0.456]	3.00	[1.5, 9.2]
39	0.118	0.102	[0.028, 0.300]	1.57	[1,3]	0.107	0.094	[0.009, 0.300]	2.61	[1.3, 7.2]
40	0.167	0.149	[0.040, 0.386]	1.70	[1,4]	0.099	0.080	[0.007, 0.296]	2.69	[1.2, 10.7]
41	0.082	0.068	[0.021, 0.214]	1.94	[1,4]	0.096	0.079	[0.006, 0.295]	3.20	[1.5, 11.5]
42	0.133	0.107	[0.033, 0.343]	1.87	[1,4]	0.100	0.078	[0.006, 0.321]	2.73	[1.3, 9.7]
43	0.143	0.130	[0.026, 0.336]	2.47	[1,8]	0.128	0.105	[0.007, 0.418]	3.40	[1.4, 33.4]
44	0.070	0.061	[0.016, 0.191]	2.04	[1,5]	0.125	0.104	[0.010, 0.384]	2.88	[1.3, 9.6]
45	0.136	0.116	[0.030, 0.328]	1.45	[1,3]	0.125	0.104	[0.007, 0.377]	2.55	[1.2, 8.0]

Note: Bandwidth (BW) is measured by $|\hat{\tau}_U - \hat{\tau}_L|$ in the band-TAR model:

$$\Delta p_{ij,t} = \begin{cases} \tau_U(1-\sum_{k=1}^{K}\beta_{k,ij}) + \sum_{k=1}^{K}\beta_{k,ij}p_{ij,t-k} + \varepsilon_{ij,t} & \text{if } \; p_{ij,t-1} > \tau_U \\ \varepsilon_{ij,t} & \text{if } \; -\tau_L \leq p_{ij,t-1} \leq \tau_U \\ -\tau_L(1-\sum_{k=1}^{K}\alpha_{k,ij}) + \sum_{k=1}^{K}\alpha_{k,ij}p_{ij,t-k} + \varepsilon_{ij,t} & \text{if } \; p_{ij,t-1} < -\tau_L \end{cases}$$

where τ_U and τ_L represent the upper and lower bounds of the inaction band and $q^k_{ij,t} = |\ln P^k_{i,t} - \ln P^k_{j,t}|$ is the (log) price differential between cities i and j at time t. The long-run average price differential (LAPD) is measured by $\hat{\kappa}$ in the AR model:

$$\Delta q^k_{ij,t} = \kappa(1-\alpha) - (1-\alpha)q_{ij,t-1} + \sum_{s=1}^{p}\delta_j \Delta q^k_{ij,t-s} + \varepsilon^k_{ij,t}.$$

BW and LAPD estimates are the mean and median estimates across the 1,128 ($=\frac{48\times 47}{2}$) for each product. Half-lives are in quarters.

Table 4: Cross-product BW and LAPD estimates by cities

	city name	BW mean	BW median	LAPD mean	LAPD median
1	ABILENE	0.155	0.121	0.150	0.095
2	AMARILLO	0.156	0.126	0.133	0.090
3	ATLANTA	0.150	0.115	0.141	0.085
4	CEDAR RAPIDS	0.147	0.112	0.144	0.092
5	CHARLOTTE	0.147	0.113	0.138	0.081
6	CHATTANOOGA	0.149	0.117	0.217	0.078
7	CLEVELAND	0.146	0.112	0.123	0.089
8	COLORADO SPRINGS	0.152	0.109	0.108	0.081
9	COLUMBIA	0.154	0.123	0.111	0.076
10	COLUMBIA	0.153	0.125	0.131	0.083
11	DALLAS	0.152	0.123	0.134	0.084
12	DENVER	0.165	0.124	0.261	0.097
13	DOVER	0.148	0.109	0.121	0.098
14	FAYETTEVILLE	0.149	0.107	0.115	0.085
15	GLENS FALLS	0.166	0.123	0.144	0.099
16	GREENVILLE	0.146	0.109	0.196	0.083
17	HOUSTON	0.150	0.110	0.282	0.093
18	HUNTSVILLE	0.149	0.116	0.111	0.079
19	JONESBORO	0.153	0.120	0.134	0.093
20	JOPLIN	0.163	0.127	0.182	0.118
21	KNOXVILLE	0.145	0.110	0.133	0.089
22	LEXINGTON	0.139	0.100	0.121	0.076
23	LOS ANGELES	0.177	0.146	0.265	0.149
24	LOUISVILLE	0.163	0.117	0.225	0.095
25	LUBBOCK	0.155	0.117	0.124	0.086
26	MEMPHIS	0.167	0.133	0.107	0.075
27	MOBILE	0.140	0.109	0.123	0.080
28	MONTGOMERY	0.140	0.103	0.101	0.073
29	ODESSA	0.150	0.120	0.136	0.085
30	OKLAHOMA CITY	0.142	0.103	0.130	0.082
31	OMAHA	0.142	0.105	0.131	0.094
32	PHILADELPHIA	0.173	0.133	0.259	0.166
33	PHOENIX	0.150	0.118	0.128	0.094
34	PORTLAND	0.167	0.122	0.196	0.136
35	RALEIGH	0.144	0.106	0.157	0.087
36	RENO-SPARKS	0.161	0.130	0.156	0.117
37	RIVERSIDE	0.166	0.134	0.276	0.120
38	SALT LAKE CITY	0.169	0.125	0.116	0.086
39	SAN ANTONIO	0.181	0.141	0.242	0.103
40	SOUTHBEND	0.154	0.117	0.239	0.099
41	SPRINGFIELD	0.165	0.133	0.133	0.082
42	ST. CLOUD	0.146	0.110	0.153	0.093
43	ST. LOUIS	0.152	0.115	0.114	0.081
44	SYRACUSE	0.168	0.132	0.131	0.097
45	TACOMA	0.182	0.151	0.170	0.128
46	TUCSON	0.152	0.120	0.182	0.095
47	WACO	0.160	0.120	0.140	0.088
48	YORK	0.141	0.105	0.120	0.089

Note: Entries represent the mean and median values across 45 products for given city.

Table 5: Pooling regression by product groups

sample	Specification 1 regressor	BW	LAPD	Specification 2 regressor	BW	LAPD
Full	log(DISTANCE)	0.006‡	0.019‡	TC	0.015‡	0.067‡
				NTC	0.006‡	0.013‡
	RINCOME	0.110*	0.098	RINCOME	0.110*	0.106
	POPULATION	0.035‡	0.132‡	POPULATION	0.035‡	0.130‡
	SAME STATE	-0.013‡	-0.016‡	SAME STATE	-0.014‡	-0.007
	Adj-R^2	0.211	0.131	Adj-R^2	0.211	0.131
Category 1						
Perishable	log(DISTANCE)	0.012‡	0.026‡	TC	0.036‡	0.094‡
				NTC	0.010‡	0.018‡
	RINCOME	0.234*	0.055	RINCOME	0.236*	0.066
	POPULATION	0.071‡	0.069‡	POPULATION	0.071‡	0.066‡
	SAME STATE	-0.020‡	-0.021‡	SAME STATE	-0.017‡	-0.007
	Adj-R^2	0.233	0.212	Adj-R^2	0.233	0.213
Non-perishable	log(DISTANCE)	0.006‡	0.018‡	TC	0.013‡	0.059‡
				NTC	0.007‡	0.013‡
	RINCOME	-0.008	-0.007	RINCOME	-0.010	-0.001
	POPULATION	0.028	0.043‡	POPULATION	0.028	0.041*
	SAME STATE	-0.016‡	-0.005‡	SAME STATE	-0.018‡	0.001
	Adj-R^2	0.139	0.154	Adj-R^2	0.139	0.154
Service	log(DISTANCE)	0.000	0.011‡	TC	-0.005	0.045‡
				NTC	0.003‡	0.005†
	RINCOME	0.122	0.232	RINCOME	0.119	0.239
	POPULATION	0.015	0.293‡	POPULATION	0.016	0.291‡
	SAME STATE	-0.007	-0.001‡	SAME STATE	-0.011*	0.009
	Adj-R^2	0.121	0.125	Adj-R^2	0.121	0.126
Category 2						
Not-locally	log(DISTANCE)	0.013‡	0.028‡	TC	0.043‡	0.098‡
				NTC	0.010‡	0.020‡
	RINCOME	0.206	0.036	RINCOME	0.210	0.047
	POPULATION	0.074*	0.078‡	POPULATION	0.073*	0.075‡
	SAME STATE	-0.022‡	-0.022‡	SAME STATE	-0.017‡	-0.008
	Adj-R^2	0.121	0.205	Adj-R^2	0.121	0.206
Maybe-locally	log(DISTANCE)	0.007‡	0.020‡	TC	0.014‡	0.066‡
				NTC	0.008‡	0.015‡
	RINCOME	0.005	0.040	RINCOME	0.003	0.046
	POPULATION	0.040*	0.047†	POPULATION	0.041*	0.045†
	SAME STATE	-0.017‡	-0.007†	SAME STATE	-0.020‡	0.001
	Adj-R^2	0.148	0.146	Adj-R^2	0.148	0.146
Locally-produced	log(DISTANCE)	0.001	0.015‡	TC	-0.002	0.055‡
				NTC	0.003*	0.009‡
	RINCOME	0.165†	0.218	RINCOME	0.163†	0.225
	POPULATION	0.007	0.301‡	POPULATION	0.007	0.299‡
	SAME STATE	-0.004	-0.006	SAME STATE	-0.007*	0.003
	Adj-R^2	0.151	0.191	Adj-R^2	0.151	0.191

Note: See eqs.(2)-(3) for regression equations. 'BW' denotes bandwidth estimates from an asymmetric TAR model in (??). ‡, †, and * respectively indicate statistical significance at the 1%, 5%, and 10% error levels and heteroskedasticity robust standard errors are used. Numbers in the curved bracket represent the number of observations in each regression.

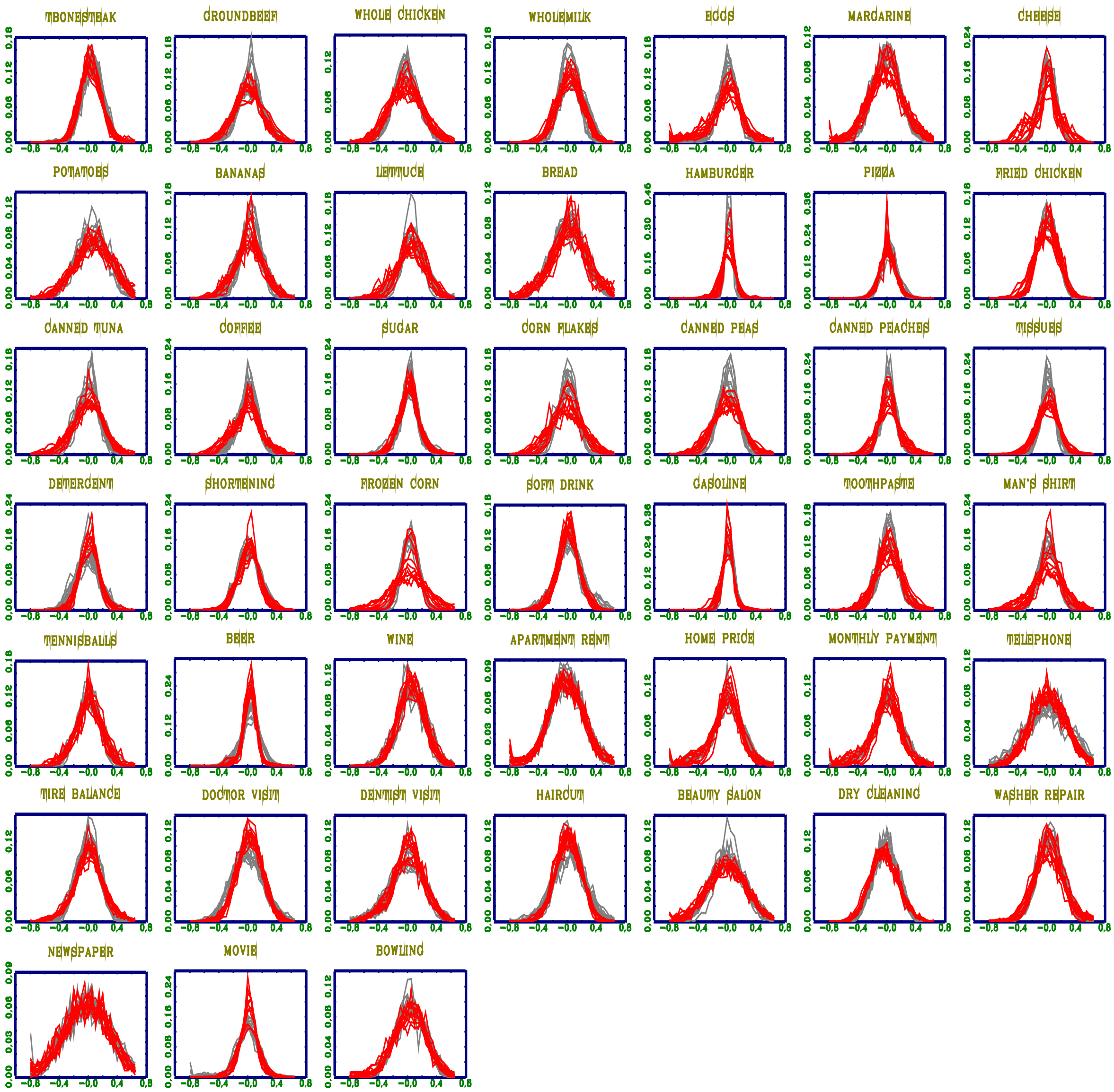

Figure 1: Empirical distributions of annual intercity price differences

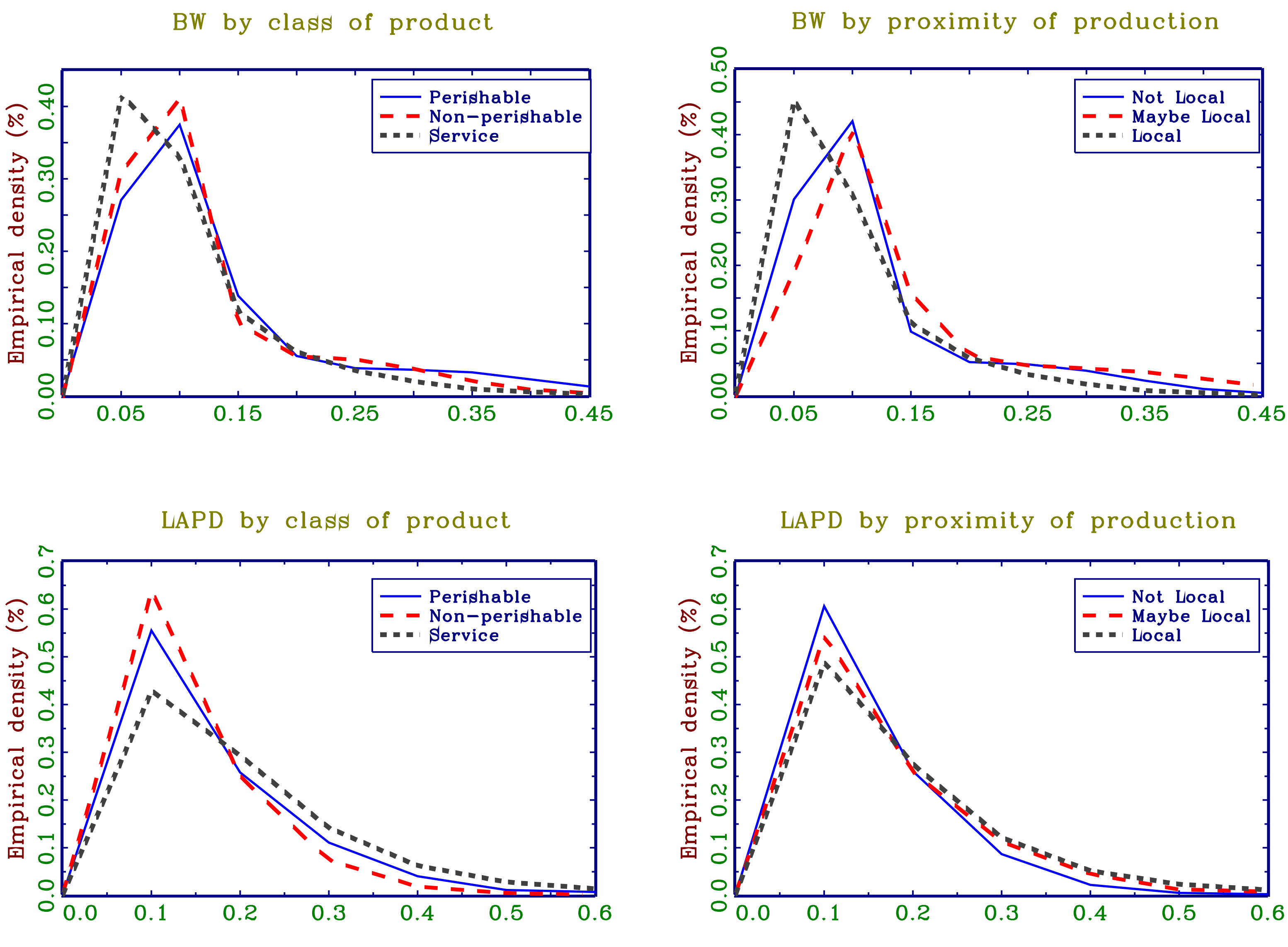

Figure 2: Empirical densities of BW and LAPD by product categories

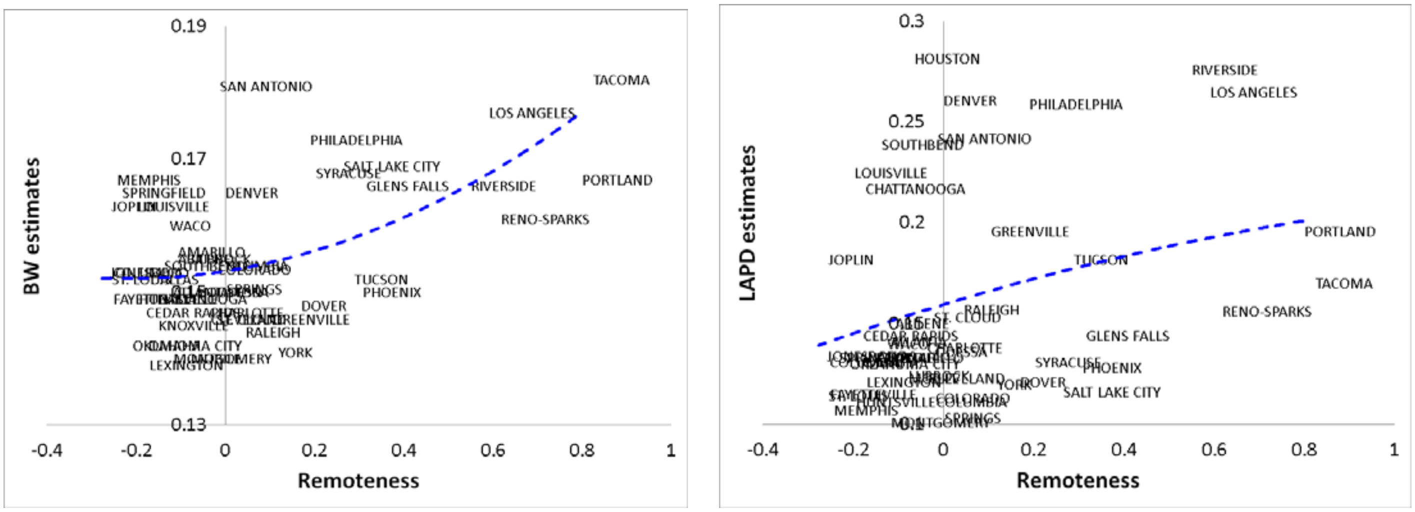

Figure 3: Scatterplots of remoteness and market segmentation

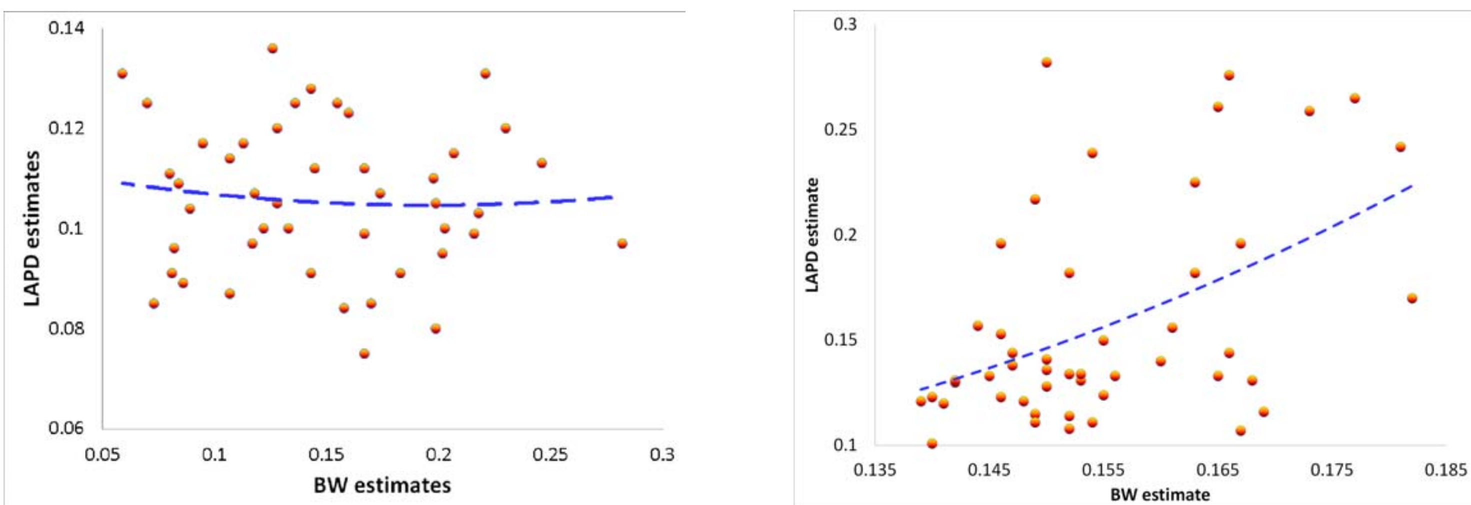

Figure 4: Scatterplots of two metrics of market segmentation across products (on the left) and across cities (on the right

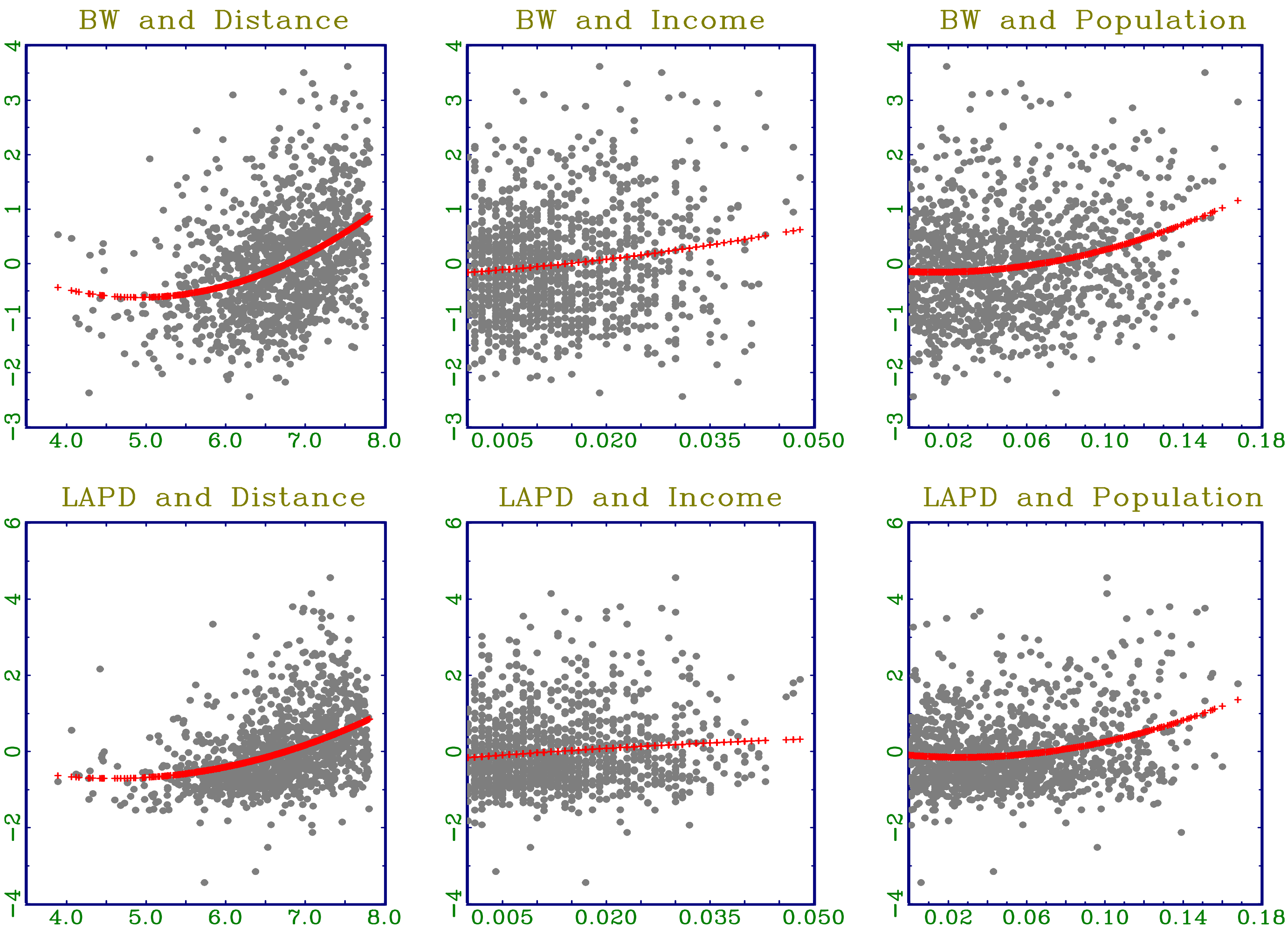

Figure 1: Scatterplots of common factors of BW (top) and LAPD (bottom) against potential explanatory variables

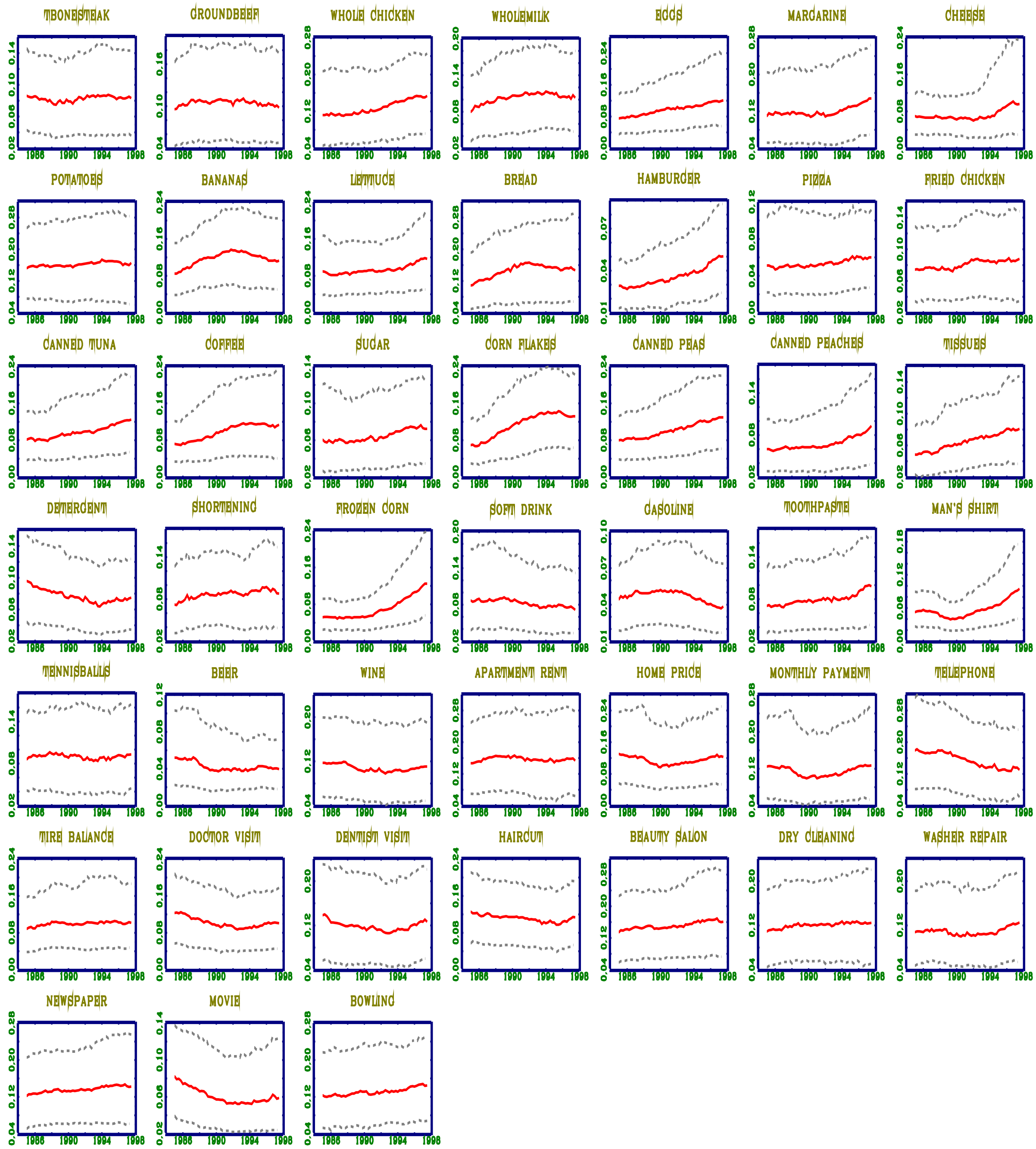

Figure 2: Estimated 12-year rolling long term average price differentials (LAPDs) by product