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 behind 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 city-pair price differences within the framework of both linear autoregressive (AR) and nonlinear threshold autoregressive (TAR) models. We find that the magnitude of market segmentation varies from one product to another, but even more across city-pairs in each product. Contrary to a widespread perception, market segmentation within the U.S. is not necessarily larger for nontradable 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, differences in wage and rent, type of product and proximity to marketplace. Distance, which captures more than transport costs, turns out to be the most salient factor even after controlling for a range of other potential factors. The effect of distance, however, varies substantially across products, with perishable products and locally-produced products showing larger distance effect on market segmentation. We find that the magnitude of market segmentation has been somewhat stable during the sample period, but intercity price differences have become more sensitive to distance over time in many products under study.

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1. Introduction

Are consumer markets in the U.S. integrated? If so, to what extent? 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 (e.g., Engel and Rogers 2004, Giri 2012). In highly integrated markets, therefore, prices for similar products in different cities should not be very different.[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] Mainly due to the lack of appropriate metric of market segmentation, however, not much is known about the extent to which markets are segmented, in particular how markets are segmented along various products. Moreover, no consensus has yet been reached about the 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. are very informative about 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 two-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 price differences for

[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). Although popularly used in the literature, this demand-side approach to measuring market segmentation on the basis of price differences could be incomplete without the information on quantity (e.g., Boivin, Clark and Vincent 2012). In the absence of the data on quantity, we follow much of the literature by utilizing price-based metrics of market segmentation.

[2] This is particularly the case for currency union where prices in different economies are quoted in a single common currency. As clearly mentioned 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 reducing transaction costs and ultimately by removing trade barriers. According to Hsieh and Moretti (2015), 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.

[3] Use of intra-national price data helps us 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, non-trivial price differences exist between geographically distant locations even for goods sold online (e.g., Gorodnichenko and Talavera 2011, Boivin, Clark and Vincent 2012). For a dissenting view, see Cavallo, Neiman and Rigobon (2014) who conclude that the law of one price (LOP) holds in the EZ.

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 of limited value. A more appropriate way to quantify the extent of market segmentation across cities is to utilize the information embedded in the dynamic behavior of the inter-city price differentials.

In addition to period-average price differences (hereafter, PPD), 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 by limiting arbitrage opportunities. In consequence, a certain price differential band exists between two cities within which price difference persists, while it reverts toward the band once the price difference falls outside the band. The width of this 'band of inaction', or bandwidth (BW), can therefore be viewed as a potential 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 inaction band. 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 can also be generated by additional factors such as 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. 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 popularly used in the literature (e.g., Ceglowski 2004, Goldberg and Verboven 2005). Secondly, and possibly more importantly, our tests for the linearity of intercity price differential dynamics yield mixed evidence on nonlinearity. So, it is informative to compare the results from the measures based on both linear AR and nonlinear TAR models.

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 conducive to market segmentation. Specifically, our metrics of market segmentation are regressed onto a set of candidate product and city-pair specific explanatory variables, including product types and proximity of production to marketplace, distance - generally viewed as a proxy for transport costs - and differences in wages, rents and city sizes. Consideration of these factors

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

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. Wage and rent differentials are commonly cited sources of market segmentation in light of their impact on production costs via non-traded input costs. It is also well established that labor market segmentation leads to segmentation in product markets, mainly through the channels of wage and other local costs such as rents.[5] City size differences, often proxied by population or population density differences, may also help explain market segmentation. Larger cities, typically with more competitive market environments, tend to have lower markups and hence lower prices (e.g., Handbury and Weinstein 2014, Melitz and Ottaviano 2008).[6]

Our work, built on a long literature studying the 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 to 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 TAR and AR models, their focus rests on finding evidence of mean reversion *per se* rather than quantifying the extent of market segmentations. In addition, they do not identify potential driving forces behind the observed intercity price differentials.

We find a non-negligible amount of market segmentation within the U.S., as evidenced by the sizable and persistent differentials in intercity prices. The extent of market segmentation estimated from our metrics, however, varies widely not only across the 45 products but also across city-pairs for each product. The average BW estimated from more than 50,000 TAR models, for example, exhibits a large dispersion across products, ranging from 5.9% for a *McDonald's Hamburger* to 28.2% for *Potatoes*. The large variation of market segmentation with each product across the 1,128 city-pairs is also noticeable. Interestingly, our measures of market segmentation, in particular our BW estimates, are not necessarily larger for non-tradable services compared to traded goods, at odds with the widespread view that prices differentials are greater for products that are less traded. A qualitatively similar picture is painted when LAPD is used as the metric of market segmentation, although the two metrics of market segmentation match more closely at the city level than at the product level.

When we parse out potential drivers of the market segmentations, we find that distance is the most salient factor. Markets are more segmented (i.e., BW and LAPD are larger) for city-pairs that are farther apart, even after controlling for differences in wages, rents and city sizes. Distance is a significant explanatory factor even for "non-tradable" services. The quantitative effect of distance on market segmentation, however, varies substantially across products, with perishable products and non-locally produced products showing larger distance effect on market segmentation. Although we find weak evidence that the extent of market

[5] Per capita income is also a good explanatory variable for market segmentation, but it is not considered in our analysis due to its high correlation with wage.

[6] 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 wage rate and market competition. This is an instance of third-degree price discrimination.

segmentation has varied over time, intercity price differences have become more sensitive to distance over time for many products under study.

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 non-transport cost component is more significant for non-traded service. This is consistent with our prior intuition that markets for non-traded services are primarily segmented by non-trade cost factors such as local costs or labor market, rather than by transport costs. Wage and rent differences between cities also turn out to be significant for explaining market segmentation in most cases under study. By contrast, relative city-size, measured by population density difference, appears to have little explanatory power. We also find some evidence of state border effect on market segmentation, as the extent of market segmentation is smaller for the city-pairs in the same state.

The remainder of this paper is structured as follows. The next section briefly outlines the ACCRA data used in the paper and presents some preliminary analysis of the time series 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 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 market segmentation across cities and products. This section also investigates the stability in the extent of market segmentation over time and explores time-varying behavior of distance effect on price differences. Section 5 concludes the paper. The Appendix contains a detailed description of the data.

2. Data and descriptive statistics

2.1. The Data

Our price data are 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 numerous food products to a lower rate of tax or exempt it altogether. The data set, albeit with different sample spans, was also adopted in a number of prior related studies (e.g., Parsley and Wei 1996, O'Connell and Wei 2002, Crucini, Shintani and Tsuruga 2012). After dropping price series with missing observations for more than two consecutive quarters[7], we end up

[7] 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

with price data for 45 goods and services for 48 cities that appeared in roughly 90% 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.[8] Since the results on relative prices are known to be sensitive to the choice of numeraire (e.g., Cecchetti, Mark and Sonora 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 (= $(48 \times 47)/2$) city-pairs for 45 products). In the regression analysis, we augment our price data with city level characteristics, as well as product characteristics, which are extracted from the various sources listed in Table A.2 in the Appendix.

Our dataset is notable for the broad range of consumer products, both goods and services, included in it. As described in Table A.1 in the Appendix, the products in our dataset range 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 common practice in the literature (e.g., Parsley and Wei 1996), these products are grouped into large categorical classifications based on product types, such as perishables (P), non-perishables (N) and services (S) as presented in the third column of Table A.1. Along the lines 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 grounds. 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 facilitates price comparability across geographic locations and highlights the role of price differentials in explaining market segmentation.[9] Since the data are absolute prices for specific

set of the interpolated data is similar to the information set of the original data (e.g., Sarno, Taylor and Chowdhury 2004). Our conclusions are virtually unaltered by using nonlinear interpolation methods.

[8] 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 to 1992.Q4 that encompasses both the Great Inflation and the Great Moderation periods. Crucini, Shintani and Tsuruga (2012) used a comparable data set to ours covering 48 products and 52 cities, but with a much shorter data span of 1990 to 2007.

[9] To our knowledge, some items in our dataset are updated over time in terms of specifications (primarily by size) or replaced by a close substitute to better reflect the items purchased by the household. We view that this issue is not much consequential to the main conclusions of our study. This is partly because we use price differences in lieu of prices whose distributions remain stable over time despite changes in specifications of some products as displayed in Figure 1. Of course, 'product homogeneity' requires not just the standardization in terms of quantities and key attributes, but also the identicalness in the brand name (e.g., Choi and Choi

goods and services collected in a consistent manner by a single agency, we can not only assess the absolute size of price differences between locations, but also pin down the average level 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 (see Table A.3) around the U.S. generates a large number of time series for intercity relative prices that make meaningful cross-sectional regression analysis possible in identifying potential determinants of market segmentation at the level of city-pairs. Another merit 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.[10]

Notwithstanding the attractive features, our dataset is not without drawbacks. One disadvantage of the dataset, especially compared to the BLS data, is that the product coverage is not as comprehensive as disaggregated price indices.[11] 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 extensive 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 exists a significant variation in intercity price differentials across products, with the mean absolute price difference ranging from 6% (*McDonald's Hamburgers*) to 25.7% (*Newspapers*), seemingly at odds with the notion of price convergence among U.S. cities. Intriguingly, the price differentials tend to be larger for services than for goods - services, which are conventionally classified as non-tradables probably, are inherently less homogeneous across geographic locations. With that said, the average price difference is sizable even in the products that are easily tradable across locations, especially in

2016, Kano, Kano and Takechi 2013). Some perishable products in our data set, like *Steak* and *Eggs*, may violate this strict homogeneity condition in the absence of further information on their brand names across cities. They are nonetheless included in our analysis in the belief that they are similar across locations in terms of the key features.

[10] 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 also intend to minimize the non-trivial influence of the so-called Great Inflation on the dynamic behaviors of individual good prices.

[11] Despite the difference in the coverage of commodities and the geographic boundaries, however, the ACCRA data and the BLS data are known to produce quite similar results (e.g., Schoeni 1996).

some grocery products. 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*. This size of average intercity price difference observed in some traded products implies that tradability alone may not fully account for the intercity price differences.

Second, in each product we notice a wide dispersion of price difference across city-pairs. 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 more than 20 percentage point. The cross-city dispersion of price differences also varies significantly across products. The difference between the 90^{th} and 10^{th} percentiles of city-pair price difference reaches more than 30 percentage point for *Newspapers*, while it is less than 5 percentage point for *McDonald's Hamburgers*, suggesting that intercity price gap is less dispersed for more homogeneous goods than for intrinsically more heterogeneous service products. This sentiment is confirmed by the cross-city dispersion (measured by standard deviations) of the intercity price differences which differ significantly across products, ranging from 0.054 (*Gasoline*) to 0.166 (*Potatoes*). Even among relatively homogeneous products such as *Potatoes* and *Margarine*, however, quite a wide cross-city dispersion is noticed, casting doubt on the notion that consumer markets in the U.S. are integrated.

A visual representation of this message is conveyed in Figure 1 where the empirical distributions of annualized inter-city price differentials (q_{ijt}^{k}) are plotted for the entire sample period. Simple visual inspection of the graph suggests that the inter-city price differentials are roughly symmetrically distributed around zero for all products. Evidently, the breadth of distribution differs considerably 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 is more dispersed for the goods that are less tradable and that use more nontraded inputs to produce (e.g., Crucini, Telmer and Zachariadis 2005). More importantly, the distributions of the inter-city price differentials appear to be quite stable over time in almost all of the products, suggesting a relatively time-invariant pattern of market segmentation.

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

Our preliminary data analysis reveals that retail price differentials across U.S. cities are nontrivial and persist over time, with a significant cross-product variation. In view of the observed persistence in price differentials, it is illuminating to examine whether or not the price differences revert toward a certain mean level over time. If price differentials are mean-reverting toward a non-zero mean level, then the nonzero long-run mean level can be viewed as reflecting the extent of market segmentation. It is equally instructive to establish whether the mean-reverting patterns are better characterized by linear or nonlinear dynamic models.

To delve into the mean reversion of inter-city price differentials, 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 (at 10% significance level) out of 1,128 city-pairs in each product. Our results seem to yield mixed evidence of mean reversion in inter-city price differentials. The rejection rates vary widely across products with 34.5% to 69.6% (for the ADF test) and 36.5% to 76.7% (for the DF-GLS test). This mixed evidence on mean-reversion, however, could result from stationary but nonlinear behavior of intercity price differentials (e.g., Michael, Nobay and Peel 1997). As illustrated by Choi and Moh (2006), standard unit-root tests including the ones adopted here have poor discriminatory power when they are applied to nonlinear but stationary time series. It can be therefore surmised that log price differentials across cities are indeed stationary, as evidenced from the fairly short half-lives of one to four quarters reported in Table 3.

This leads us to explore whether the movements of inter-city price differentials are better characterized by nonlinear models than by linear model specifications. Here we consider three popular linearity tests under the null hypothesis of a linear AR model against the alternative of threshold-type nonlinearity: Tsay's (1989) test, Dahl and Gonzalez-Rivera's (2003) LM test and Hansen's (1997) test. As presented in the right-hand panel of Table 2, our results offer some evidence of nonlinearity but the evidence is not strong enough to draw any conclusive inference on the nonlinearity. The average rejection rates of the three tests (at 10% significance level) are all below 50% with a large cross-product variation in the range of 25.7% and 80.2%. Given the inconclusive evidence on the nonlinearity, we believe that it is best to consider both linear and nonlinear models in extracting information concerning market segmentation, despite compelling theoretical justifications for relative prices to be intrinsically nonlinear.[12]

3. Metrics of market segmentation

We infer the degree of market segmentation from price differentials between locations that do not disappear in the long run. The mixed evidence on the linearity of price differences renders us to consider two competing time series models that are known to offer intriguing intuition on measuring long-lasting price differentials: nonlinear TAR model and linear AR model.

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

3.1. Asymmetric band-TAR model and bandwidth (BW)

We consider the following asymmetric Band-TAR model, with special interest placed on the key parameters $(\tau^k_{L,ij},\, \tau^k_{U,ij})$.[13]

$$\Delta q^k_{ij,t} = \begin{cases} \tau^k_{U,ij}(1-\beta^k) - (1-\beta^k_{ij})q^k_{ij,t-1} + \sum_{h=1}^{m} \beta^k_{h,ij}\Delta q^k_{ij,t-h} + \varepsilon^k_{ij,t} & \text{if } \tau^k_{U,ij} < q^k_{ij,t-1} \\ \varepsilon^k_{ij,t} & \text{if } \tau^k_{L,ij} \le q^k_{ij,t-1} \le \tau^k_{U,ij} \\ \tau^k_{L,ij}(1-\gamma^k_{ij}) - (1-\gamma^k_{ij})q^k_{ij,t-1} + \sum_{h=1}^{m} \gamma^k_{h,ij}\Delta q^k_{ij,t-h} + \varepsilon^k_{ij,t} & \text{if } q^k_{ij,t-1} < \tau^k_{L,ij} \end{cases} \quad (1)$$

where $\varepsilon^k_{ij,t}$ represents the error term that could be heteroskedastic. The underlying logic to this model is that price differentials between locations would revert toward mean outside some range or band, while they follow a random walk process within this range. Since $\tau^k_{U,ij}$ and $\tau^k_{L,ij}$ denote the upper and lower bounds of the inaction band, the width of inaction band or bandwidth (hereafter, BW) is measured by $[\tau^k_{L,ij}, \tau^k_{U,ij}]$ and hence non-zero bandwidth indicates a segmented market (e.g., Sarno, Taylor and Chowdhury 2004).[14] 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. Note that this model specification allows the dynamics of the process outside the threshold to differ depending on whether deviations occur above or below the threshold 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 to 5) reports the summary statistics of the BW estimates by product - mean, median, 5^{th}- and 95^{th}-percentiles of $(\hat{\tau}^k_U - \hat{\tau}^k_L)$, 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 sizable and vary widely both across products and across city-pairs. On the product domain, the average BW estimate ranges 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

[13] While TAR models are suitable for describing the nonlinear behavior of relative prices at the individual good level, smooth transition autoregressive (STAR) models are known to better characterize the nonlinear behavior of relative prices using price indices for a basket of goods and services (e.g., Michael, Nobay and Peel 1997, Taylor and Taylor 2004).

[14] 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. Here we simply point out the main characteristics of eq.(1) and refer the reader to a number of previous studies (e.g., Obstfeld and Taylor 1997, Imbs, Mumtaz, Ravn and Rey 2003, O'Connell and Wei 2002) for a rigorous foundation of this equation. While symmetric TAR models ($|\tau_{L,ij}| = \tau_{U,ij}$ and $\gamma^k_{ij} = \beta^k_{ij}$) 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 a symmetric response. 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 $\tau^k_{U,ij} = \tau^k_{L,ij} = 0$ and $\gamma^k_{ij} = \beta^k_{ij}$.

band.[15] Such average statistics, however, provide only partial information on the actual degree of market friction as they mask an enormous degree of heterogeneity across city-pairs within each product. Indeed, the BW estimates display an extensive variation within each product, typically with a greater dispersion for the products with a larger average BW. Take *Potatoes* for example, the city-pair BW is in the broad range between 6.1% and 54.9%. This may suggest the importance of location-specific factors in explaining market segmentation. The large BW estimates for many food-related items, for which sales taxes are typically either zero or very low, suggests that differences in sales taxes are not an important explanation of consumer market segmentation (e.g., Besley and Rosen 1999).

Intriguingly, the BW estimates for service products, conventionally labeled as non-tradables, are not necessarily larger than those of tradable goods. In theory, prices in two markets should differ more for products that are less traded (e.g., services) because shocks to those prices may persist longer. One might therefore expect to find larger BWs for non-traded services, and goods that have a larger proportion of non-traded inputs (Crucini, Telmer and Zachariadis 2005). In our data, however, the average BW for service products like *Dry Cleaning* (8.2%) and *Movies* (7.0%) is far smaller than that for typical tradable goods such as *Lettuce* (24.6%), *Bread* (22.1%), and *Canned Peas* (20.7%). This finding challenges the common perception on a higher degree of market segmentation in service products that are typically produced locally and hence less tradable.[16]

The top panel of Figure 2 visualizes this point by plotting the empirical distribution of BW estimates for three sub-groups of product: perishables (P), non-perishables (N), and service (S). As shown in the top-left panel of Figure 2, the distribution of BW is roughly similar among the three product groups, indicating little difference in the distribution of the market segmentation measure between service and more tradable products. This is perhaps because every product virtually contains some non-tradable component, including labor which is highly non-tradable. Our results are consistent with the recent finding by Gervais and Jensen (2015) that many service industries have comparable trade costs to manufacturing industries. It also reinforces our original belief that transaction costs are not the sole driving force behind the segmentation of consumer markets. As displayed in the top-right panel of Figure 2, we reach

[15]In comparison with the previous studies based on the symmetric TAR model (e.g., Obstfeld and Taylor 1997, O'Connell and Wei 2002), our bandwidth estimates appear to be somewhat larger. The discrepancy can be attributable to the difference in TAR model specifications. 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% to 6%, which correspond to 2% to 12% in the asymmetric TAR model. O'Connell and Wei (2002) report 5% to 12% symmetric BW for the goods that are not locally produced. In an international context, Sarno, Taylor and Chowdhury (2004) document a wide sectoral variation of bandwidth, ranging from 1% for paper products to 20% for food, beverages and tobacco.

[16]Since products with large fluctuations of relative prices tend to have larger BWs, one may be tempted to attribute this anomalous result to the inherently large variation in the prices of tradable goods. However, there is no meaningful association between the volatility of price *per se* (p_{it}) and the volatility of relative price ($p_{it} - p_{jt}$). For example, gasoline prices fluctuate considerably over time in each city due to ever-changing market factors, but intercity differences of *gasoline* prices do not vary much over time probably because *gasoline* prices in two cities tend to co-move closely in response to common shocks.

similar conclusions 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. The distribution of 'locally produced' products is located to the left of that of 'not locally produced' products, suggesting that market segmentation is smaller for services and other locally produced products.

We also note 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, the extent of market segmentation in cities appears to hinge on their geographic location. To be more specific, coastal cities which are farther away from other cities, such as L.A., Tacoma and Philadelphia, tend to have larger BW estimates, 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.

When it comes to the deviations that are outside the bands, we find that they are relatively short lived. That is, once price deviations exceed the upper or lower threshold bounds, prices are relatively quickly pushed back towards the band of inaction in most cases under study. The average half-life (HL) estimate is of the order of just one quarter for the vast majority of products, indicating that it takes only 3 months for the impact of a shock to decay by half when 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 (presented in the last two 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 deducing market segmentation from the dynamic behavior of price differences is to estimate *long-term average price differentials* (LAPD) using a standard linear autoregressive (AR) model (e.g., Goldberg and Verboven 2005):

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

where $q^k_{ij,t}$ is the (log) price differential of product k between cities i and j at time t. The constant term ($\kappa^k_{ij}(1-\rho^k_{ij})$) captures city-pair fixed effects, i.e., time-invariant price differentials between cities. As noted by Goldberg and Verboven (2005), these fixed effects may be informative about transportation costs, markup differences or unobserved quality differences that vary by destination. The speed of convergence is captured by the parameter ρ^k_{ij} with a faster reversion to the mean for a smaller value of ρ^k_{ij}. κ^k_{ij}, the long-run, systematic price differentials between city-pair i and j for product k, is a measure of market segmentation. Inter alia, the size of κ^k_{ij} reflects long-run differences in observable costs such as marginal costs and transport costs.[17]

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 the extent of market segmentation. Across products, the LAPD estimates range between 7.5% (*Toothpaste*) and 13.6% (*Dentist's Visit*). As in the case of BW estimates, LAPD estimates exhibit a wider dispersion across city-pairs in each product. Long-run price differences of this magnitude can be hardly compatible with the notion of market integration within national a border.

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 explore this issue, we plot in Figure 3 the average BW estimates against the average LAPD estimate by products (on the left) and by cities (on the right). The plots display a clear positive association between the two metrics at the city level, but a weak association at the product level, indicating that the two measures are in more agreement at the city level than at the product level. Since this implies that the two measures of market segmentation may reflect different aspects of market segmentation at the product level, comparing the results from the two different metrics of market segmentation may help contribute to a better understanding of the issue at hand.

4. Sources of market segmentation

The pervasive evidence on consumer market segmentation in the U.S. naturally raises the question of what factors may account for it. In this section, we identify the factors conducive to market segmentation by exploiting the information embedded in the wide heterogeneity of the diverse measures of market segmentation.

4.1. Regression analysis

We first explore both city-pair specific and product specific explanatory variables. The main city-pair factors are distance between cities, wage and rent differences, and relative city-sizes. For the product specific factors, we consider product types and proximity of production to markets, which have been identified as important drivers of market segmentation in the relevant literature. Since trade costs embrace local distribution costs (e.g., Choi and Choi 2014, 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 the 45 products into three types - perishables (P), non-perishables (NP) and services (S). It is

[17] Interestingly, Goldberg and Verboven (2005) interpreted the constant term ($\kappa_{ij}^k(1-\rho_{ij}^k)$) 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).

conceivable that market segmentation will be smaller for products that are more tradable. We also follow O'Connell and Wei (2002) and 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, wages and markups. Consequently 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 three metrics of market segmentation (BW, LAPD and PPD) are regressed onto a set of candidate explanatory variables. Here, we consider two model specifications of regression depending on whether we include distance per se or its decomposition into transport cost (TC) and other cost components (NTC).[18]

$$\widehat{MS}_{ij}^{g} = \rho_0 \log(DIST_{ij}) + \rho_1 DISTDUMMY_{ij} + X\beta + \varepsilon_{ij}, \quad \text{(Specification 1)} \quad (3)$$

$$\widehat{MS}_{ij}^{g} = \alpha_1 TC_{ij} + \alpha_2 NTC_{ij} + X\beta + \varepsilon_{ij}, \quad \text{(Specification 2)} \quad (4)$$

where $\widehat{MS}_{ij}^{k}$ represents the metrics of market segmentation between cities i and j for product group g (where $g = P, NP, S$) 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 $DIST_{ij}$ varies across city-pairs but not across products. $DISTDUMMYij$ is a distance dummy variable which takes a value of one if cities i and j are less than 500 miles apart and zero otherwise.[20] ρ_1 is therefore expected to enter with the negative sign. X denotes a set of other explanatory variables, $X = \{WAGE_{ij}, RENT_{ij}, POPDENS_{ij}, SAMESTATE_{ij}, D_k^P, D_i^C, D_j^C\}$, where '$WAGE_{ij}$', '$RENT_{ij}$' and '$POPDENS_{ij}$' respectively denote city-pair differences in wage, rent and population density computed by $[max(z_i, z_j) - min(z_i, z_j)]/max(z_i, z_j)$ in which $z_h = (1/T)\sum_{t=1}^{T} z_{ht}$ denotes the average of the corresponding variable over the sample period for city h. The difference in population density ('$POPDENS_{ij}$') captures the effect of relative market size. As discussed earlier, the coefficients for '$WAGE_{ij}$', '$RENT_{ij}$' and '$POPDENS_{ij}$' are expected to have a positive effect on the size of market segmentation.

'$SAMESTATE_{ij}$' represents an intra-state dummy variable which takes on the value of one if two cities i and j are in the same state and zero otherwise. As an inverse measure of

[18]Since estimated values are used as dependent variable, our regression is subject to the issue of the so-called estimated dependent variables (EDV) problem which is addressed 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 are skewed to the right as can be seen from Figure 2. Using quantile regression analysis, we confirm that our results are sturdy to the skewed nature of dependent variable.

[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 measures of distance, however, Engel and Rogers (1996) document that the results are largely similar.

[20]The distance dummy variable captures the nonlinear effect of distance. A distance of 500 miles is the approximate daily driving limit for a commercial driver (11-hour driving limit per day).

state border effect, this dummy variable 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 wage, rent and population density, 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.[21]

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), by utilizing the data on inter-spatial trade cost constructed by Allen and Arkolakis (2014). Whereas the conventional literature tends to interpret distance effect as solely reflecting TC, distance may induce price wedges between locations via additional channels in view of the growing evidence that other factors may also operate on the geographic distance (e.g., Choi and Choi 2016). Since NTC may contain information on local distribution costs and mark-up rates that are known to constitute a large component of final consumer prices, the distinction between the two channels may provide additional insights into the driving forces behind market segmentation.[22]

Table 5 presents the regression results for both model specifications. The top panel sets out the results for the entire 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 are more dissimilar in terms of wages, rents and population densities. Looking at their quantitative effect, we find that a 10% increase in the distance between two cities *ceteris paribus* increases the city-pair market segmentation by around 0.03 percentage point (BW), 0.12 percentage point (LAPD) and 0.14 percentage point (PPD). Similarly, the effect of a 10% increase in the wage rate difference ('$WAGE_{ij}$') and rent difference ('$RENT_{ij}$') between two cities is to increase the size of BW-based market segmentation by 2.3% and 2.9%, respectively. By contrast, differences in population density turn out to be significant only for the PPD-based market segmentation measure, possibly because local distribution costs related to market size are better captured by wages and rents. The coefficient for '$SAMESTATE$' dummy variable takes an anticipated negative sign, indicating that two cities in the same state are likely to have a lower level of market segmentation. It is worth stressing that the BW and LAPD results are quite compatible in terms of the signs and significance of the explanatory

[21] With a high degree of clustering among the city-pair/product combinations, standard heteroscedastic robust standard errors may overstate the true standard errors and hence lower statistical significance. To get around this issue, we use 'clustered standard errors' in our pooling regression analysis. Since prices are more correlated across cities for a given product rather than across products for a given location, we estimate robust clustered s.e. by clustering observations by cities rather than by products. We thank an anonymous referee for suggesting this feature to us.

[22] Note that the regressor NTC is a residual and thus is subject to the so-called 'generated regressor problem' (e.g., Pagan 1984) that invalidates OLS-based standard errors. Since no lag terms are included in our regression analysis, however, our regression analysis is not susceptible to this problem.

variables, while the significance of explanatory variables improves using the PPD-measure. Overall, distance appears to be the most salient factor behind market segmentation in almost all the cases considered.[23]

To understand the role of product characteristics, we run separate regressions for the three product categories: perishable goods (P), non-perishable goods (NP) and services (S). The middle panel of Table 5 reports the regression results. Not surprisingly, the significance and the quantitative effect of the distance and other explanatory variables vary markedly by product type. For example, the marginal effect of distance on BW shown in the "specification 1" columns is 0.009 for perishable products while approximately zero for services. This finding squares well with the conventional wisdom that perishable products have higher transport costs as they are more easily spoiled within a short period of time, and hence their markets are more segmented by physical proximity. For non-perishable products, distance is still significant but has a smaller effect on BW than it does for perishables. By contrast, one does not expect consumers of services such as a routine visit to a doctor or a haircut arbitrage away intercity price differentials. Notice that the distance dummy variable takes a similar profile with that of distance with expected negative signs in all cases. This implies that the city-pairs within 500 miles away are likely to have a larger distance effect on market segmentation than those that are farther apart. When it comes to the other explanatory variables, '$WAGE$' and '$RENT$' are significant with the expected positive signs in most cases under consideration, whilst '$POPDENS$' is not.

Qualitatively similar results are obtained from the second model specification where the distance effect is broken down into TC and NTC components. As expected, TC is more significant for tradable goods than for non-traded service, whereas NTC is significant for both tradable and nontradable products, in line with the finding by Choi and Choi (2014) that distance contains more information than transport costs. This result may stem, in part, from the fact that service products contain a substantial amount of nontraded local inputs, but far less amount of traded component. Rent differences continue to have a significant explanatory power for all product categories, while wage differences have greater explanatory power for nontradable services. Local input costs are likely to be similar in nearby locations since many labor markets are geographically integrated (e.g., Engel, Rogers and Wang 2003). Moreover, as noted by Redding and Turner (2014), in addition to reducing transportation costs, geographic proximity may generate positive agglomeration effects, including knowledge

[23] Price difference across markets may not necessarily reflect market segmentation if it is driven by pervasive price stickiness. As emphasized in Boivin, Clark and Vincent (2012), an ideal way to test for market segmentation would be through the combined use of quantities and prices. Unfortunately, this approach is not plausible in our case due to the lack of the quantity data. Alternatively, one can control for such factors before focusing on the extent of market segmentation and its determinants by utilizing a two-stage estimation approach: first, obtain residuals by regressing the measures of market segmentation onto other control variables than distance and state dummy variables; then regress the residuals onto distance and state dummy variables. To ensure the robustness our conclusions to this issue, we adopt the two-stage approach and find qualitatively similar results on the role of distance and state dummy variables in explaining market segmentation. We thank an anonymous referee for bringing this feature to our attention.

spillovers and idea flows. In fact, it is often claimed that labor markets are still local even in the era of the internet. By contrast, difference in population density is insignificant in most cases considered.

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. The effect of distance on market segmentation is strongest in the product group that is not locally produced, while it is smallest 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 less.

4.2. Stability of market segmentation over time

Our time series model based estimates of market segmentation are obtained under the assumption that the dynamics of intercity price differences, and their long run levels or bands, do not vary significantly over time. For example, the band TAR models assume that thresholds remain stable over time. This assumption, however, could be fragile if rapid developments in transportation, logistics and information technologies affect the width of the inaction band. Given that the literature often documents a secular decline in transportation costs for goods (e.g., Redding and Turner 2014), it is worth investigating whether or not the estimates of market segmentation vary over time.

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 exhibits the evolution of kernel densities of annualized intercity price differences over the sample period. With the notable exception of *Frozen Corns* (Item 24), we find little evidence that the distribution of price dispersion has varied significantly over time in the vast majority of products, lending little credence to the argument of time-varying market segmentation.

A similar story is told from Figure 4 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 4, 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 the extent of 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 quite stable over time, without any drastic shifts or discrete changes.[24] Combined together, our evidence corroborates the use of time-invarying measures of market segmentation.

4.3. Time-varying effect of distance on intercity price differences

Given the particular importance of distance in explaining market segmentation, it is also interesting to examine whether or not the impact of distance on intercity price differences has been stable over time as in the case of market segmentation measures. In light of the pervasive evidence on the advance of technology and changes in preference over time, there seems no strong a priori reason to believe that the marginal effect of distance on market segmentation was stable in our sample. If the distance effect does vary over time, it would be interesting to know which products display the most time-variation.

To this end, we first consider the following regression model,

$$PPD_{ij,t}^{k} = \rho_0^k \log(DIST_{ij}) + \rho_1^k \log(DIST_{ij}) \cdot D_t + X_t \beta + \varepsilon_{ij,t}^k, \tag{5}$$

where $PPD_{ij,t}^{k}$ denotes the period-average price difference between cities i and j at time t for product k, X_t is the usual set of explanatory variables other than distance at time t, and D_t is a time dummy variable that takes the value of one for the period after 1997, which is approximately a middle point of our sample period. This specification allows the effect of distance on intercity price differentials to differ before and after 1997. As reported in Table 6, we find compelling evidence that the strength of distance effect has indeed changed after 1997 in almost all the products under study. The direction of change captured by the sign of $\hat{\rho}_1$, however, is rather mixed, although the distance effect appears to have increased after 1997 in the majority of products (28 out of 45 products).

The time-varying behavior of distance effect is further supported in Figure 5 which plots the annualized marginal effects of distance on PPD over the sample period for the three product groups: perishables, non-perishables, and services. The dotted line in Figure 5 represents the annualized distance effect on PPD estimated from the following regression equation, and the solid line represents its Hodrick-Prescott (H-P) filtered value.

$$PPD_{ij,t}^{g} = \rho_t^g \log(DIST_{ij}) + X_t \beta_t^g + \varepsilon_{ij,t}^g, \qquad \text{where} \;\; t = 1, ..., 25,$$

where ρ_t^g is the coefficient of interest that reflects the annualized distance effect on PPD for product group g at time t. As displayed in Figure 5, the distance effect is neither stable over time nor homogeneous over the three product groups. Not surprisingly, distance has the greatest effect in perishable goods, and the smallest effect for services. Interestingly, the strength of distance effect seems to have grown over time in tradable products, while it has declined consistently for services. The overall distance effects are slightly S-shaped over time

[24] 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.

around a value of 0.14, with an initial decline up to mid-1990s followed by a subsequent rebound.

Our finding on the increased effect of distance in tradable products obviously runs counter to our prior intuition that intercity price differences for tradable products should decline over time due to the improvement of transportation and information technologies. One possible explanation for this puzzling result is that distance effect does not arise solely from transport costs, as emphasized by Choi and Choi (2014). To the extent that the importance of the non-transport cost (NTC) component of distance relative to that of the transport-cost (TC) component has grown over time in the movement of tradable product prices, distance could matter more over time for explaining intercity price differences despite the secular decline in transportation costs for goods. Although this is an interesting avenue of research, we leave the issue to future work as it lies beyond the scope of the current study.

5. Concluding remarks

We quantified the magnitude and persistence of market segmentation in U.S. consumer markets, 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 various models, including both autoregressive and band threshold autoregressive models. We found significant and persistent level of intercity market segmentation in the U.S. consumer markets, despite the fact that relative price shocks are generally short lived. Moreover, the degree of market segmentation varies considerably across both cities and products. Contrary to the common belief, we find little evidence that the distributions of market segmentation between tradable and non-tradable products are different.

We utilized regression analyses to identify the potential drivers of market segmentation by linking the level of market segmentation to location-specific and product-specific characteristics - distance between cities, relative city sizes, wage and rent differences, type of products, and proximity of production to marketplace. Distance turns out to be the most salient factor, probably because it captures other factors in addition to transport costs as highlighted by Choi and Choi (2014). The marginal effect of distance, however, varies by product characteristics. Greater distance generates significantly higher levels of market segmentation for perishable products and products that are not locally produced. When we decompose the distance effect into the part attributable to transport costs and the remaining part due to non-transport costs, we find that markets for non-traded services are mainly segmented by the latter, while market segmentation for traded goods is driven by both components. When we look at the time-varying behavior of market segmentation, there is little evidence that our metrics for market segmentation vary significantly over time. By contrast, the impact of distance on intercity price difference turns out to have increased over time in many products under study.

Our U.S. results have some intriguing 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 generally agreed that the integration of a market for goods and services in the EZ has yet been realized. Our finding that distance accounts for the 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 A1
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 first product classification (Class1) refers to non-perishable goods (N), perishable goods (P) or services (S), while the second classification is based on the proximity of production to the market place where 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 A2

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)
Wage	Average wage per job of U.S. Metropolitan area during 1985-2009	BEA website
Rent	Average fair market rent of U.S. Metropolitan area during 1990-2009	Department of Housing and Urban Development (HUD.GOV)
Population density	Average populations of the U.S. Metropolitan area per square miles during 1980-2000	Census Bureau website

TABLE A3
City-level characteristics (period average)

City code	City name	State	Income (dollars)	Population (thousands)	Pop. Density (per sq. miles)	CPI	Remoteness	Price volatility
1	ABILENE	TX	16,938	140	1,017.6	0.814	0.151	0.22
2	AMARILLO	TX	17,905	218	1,782.1	0.805	0.151	0.22
3	ATLANTA	GA	21,560	4,143	3,125.7	0.925	0.138	0.23
4	CEDAR RAPIDS	IA	20,238	212	1,793.8	0.826	0.080	0.22
5	CHARLOTTE	NC	21,190	1,402	1,722.9	0.865	0.220	0.24
6	CHATTANOOGA	TN	18,196	470	1,177.1	0.844	0.083	0.25
7	CLEVELAND	OH	16,100	2,173	6,693.5	0.903	0.224	0.24
8	COLORADO SPRINGS	CO	19,419	519	1,537.0	0.864	0.240	0.26
9	COLUMBIA	MO	18,078	139	1,355.0	0.830	0.241	0.24
10	COLUMBIA	SC	18,213	589	854.5	0.817	0.005	0.25
11	DALLAS	TX	22,536	3,423	3,017.5	0.900	0.089	0.22
12	DENVER	CO	24,482	2,082	3,293.0	0.933	0.256	0.26
13	DOVER	DE	16,840	131	1,239.7	0.901	0.426	0.25
14	FAYETTEVILLE	AR	16,449	125	1,050.7	0.768	0.003	0.25
15	GLENS FALLS	NY	16,747	124	3,940.3	0.911	0.574	0.25
16	GREENVILLE	NC	16,319	142	1,857.2	0.811	0.363	0.26
17	HOUSTON	TX	22,862	4,703	2,979.8	0.870	0.193	0.20
18	HUNTSVILLE	AL	19,450	347	882.1	0.832	0.064	0.23
19	JONESBORO	AR	14,821	93	559.1	0.749	0.000	0.23
20	JOPLIN	MO	15,555	154	1,331.4	0.760	0.003	0.22
21	KNOXVILLE	TN	18,463	646	1,849.0	0.787	0.106	0.22
22	LEXINGTON	KY	20,257	435	808.4	0.856	0.087	0.22
23	LOS ANGELES	CA	22,628	9,406	7,212.1	0.797	0.848	0.28
24	LOUISVILLE	KY	19,914	1,094	4,424.1	1.039	0.059	0.22
25	LUBBOCK	TX	16,951	245	1,626.3	1.005	0.178	0.23
26	MEMPHIS	TN	19,617	1,157	2,275.3	0.859	0.014	0.23
27	MOBILE	AL	15,404	456	1,684.0	0.904	0.179	0.22
28	MONTGOMERY	AL	18,062	334	1,216.3	0.793	0.139	0.24
29	ODESSA	TX	16,271	180	2,451.7	0.813	0.240	0.21
30	OKLAHOMA CITY	OK	19,120	1,080	744.0	0.829	0.050	0.22
31	OMAHA	NE	21,435	738	2,995.3	0.830	0.085	0.23
32	PHILADELPHIA	PA	23,417	4,435	11,822.6	0.979	0.447	0.26
33	PHOENIX	AZ	19,604	3,218	2,172.0	0.874	0.565	0.24
34	PORTLAND	OR	21,454	1,889	3,315.6	0.905	1.057	0.27
35	RALEIGH	NC	21,780	967	1,857.0	0.883	0.302	0.26
36	RENO-SPARKS	NV	24,832	337	2,062.3	0.956	0.874	0.26
37	RIVERSIDE	CA	17,365	3,345	2,784.1	0.978	0.807	0.26
38	SALT LAKE CITY	UT	18,863	111	1,542.3	0.924	0.523	0.26
39	SAN ANTONIO	TX	17,870	1,661	2,344.0	0.812	0.245	0.24
40	SOUTHBEND	IN	18,663	1,117	2,783.8	0.798	0.120	0.25
41	SPRINGFIELD	IL	20,742	2,796	1,956.3	0.807	0.027	0.23
42	ST. CLOUD	MN	16,813	169	1,663.2	0.859	0.236	0.25
43	ST. LOUIS	MO	21,488	202	6,447.4	0.848	0.004	0.25
44	SYRACUSE	NY	19,071	696	6,393.9	0.873	0.460	0.25
45	TACOMA	WA	24,715	695	3,519.2	0.881	1.082	0.26
46	TUCSON	AZ	17,189	838	2,093.5	0.855	0.546	0.24
47	WACO	TX	16,279	210	1,261.2	0.810	0.134	0.22
48	YORK	PA	20,124	383	8,184.2	0.868	0.376	0.24

NOTES: '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 Census Bureau website, 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 differenential (PPD)				std. dev
item	mean	median	[10%,90%]	std. dev	of price
1	0.081	0.070	[0.013, 0.164]	0.098	0.28
2	0.097	0.081	[0.017, 0.200]	0.130	0.28
3	0.133	0.109	[0.020, 0.286]	0.130	0.19
4	0.089	0.080	[0.014, 0.183]	0.095	0.15
5	0.143	0.092	[0.018, 0.327]	0.127	0.21
6	0.129	0.101	[0.018, 0.276]	0.140	0.25
7	0.081	0.065	[0.010, 0.177]	0.083	0.21
8	0.161	0.146	[0.022, 0.317]	0.166	0.14
9	0.102	0.086	[0.016, 0.212]	0.127	0.34
10	0.102	0.089	[0.018, 0.203]	0.143	0.18
11	0.137	0.113	[0.019, 0.280]	0.151	0.26
12	0.037	0.033	[0.006, 0.073]	0.056	0.27
13	0.053	0.039	[0.007, 0.121]	0.068	0.22
14	0.087	0.077	[0.015, 0.176]	0.088	0.15
15	0.100	0.081	[0.013, 0.207]	0.121	0.20
16	0.101	0.080	[0.015, 0.221]	0.097	0.19
17	0.069	0.053	[0.010, 0.145]	0.092	0.13
18	0.097	0.084	[0.017, 0.195]	0.119	0.29
19	0.103	0.086	[0.015, 0.218]	0.113	0.22
20	0.067	0.054	[0.011, 0.139]	0.083	0.21
21	0.066	0.055	[0.008, 0.144]	0.088	0.22
22	0.078	0.069	[0.010, 0.160]	0.095	0.27
23	0.074	0.060	[0.012, 0.158]	0.080	0.19
24	0.071	0.059	[0.009, 0.149]	0.123	0.32
25	0.086	0.066	[0.012, 0.187]	0.111	0.14
26	0.048	0.038	[0.008, 0.101]	0.054	0.37
27	0.082	0.068	[0.012, 0.169]	0.106	0.16
28	0.062	0.050	[0.009, 0.134]	0.119	0.20
29	0.085	0.070	[0.013, 0.178]	0.113	0.12
30	0.058	0.042	[0.007, 0.127]	0.064	0.37
31	0.121	0.106	[0.021, 0.247]	0.106	0.15
32	0.179	0.143	[0.024, 0.369]	0.096	0.25
33	0.162	0.112	[0.021, 0.373]	0.100	0.43
34	0.161	0.111	[0.019, 0.369]	0.102	0.28
35	0.174	0.153	[0.031, 0.353]	0.121	0.18
36	0.104	0.082	[0.015, 0.226]	0.098	0.20
37	0.101	0.083	[0.015, 0.208]	0.108	0.42
38	0.148	0.121	[0.018, 0.308]	0.113	0.36
39	0.124	0.107	[0.020, 0.255]	0.102	0.24
40	0.152	0.127	[0.026, 0.316]	0.131	0.25
41	0.121	0.104	[0.019, 0.242]	0.084	0.22
42	0.119	0.098	[0.017, 0.250]	0.111	0.28
43	0.211	0.182	[0.031, 0.438]	0.133	0.23
44	0.075	0.062	[0.012, 0.150]	0.079	0.21
45	0.140	0.125	[0.023, 0.293]	0.118	0.33

NOTES: PPD is the average absolute price differential across all 1,128 city pairs. The price differentials are calculated as $|\frac{1}{T}\sum_{t=1}^{T} p_{it}^{k} - \frac{1}{T}\sum_{t=1}^{T} p_{jt}^{k}|$, where p_{it}^{k} is the log of the price of item k in city i 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

NOTES: The entries in the unit-root test columns are the rejection frequencies of the unit-root null hypothesis for the 1,128 city-pair price differentials at the 10% significance level. The entries in the linearity test columns are the rejection frequencies of three linearity tests – the Tsay test, the Dahl and Gonzalez-Rivera (2003) test, and the Hansen test. The linearity rejection frequencies use a 10% significance level and 2,000 bootstrap 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]

NOTES: See eqs.(1) and (2) respectively for the band-TAR model in which BW is estimated and for the linear AR model where LAPD is estimated. Entries are obtained from 1,128 ($=\frac{48\times 47}{2}$) city-pair price differentials for each product. Half-lives are in quarters.

TABLE 4
Cross-product BW and LAPD estimates by city

	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

NOTES: The entries are the mean and median values of BW and LAPD across the 45 products for each city.

TABLE 5

Pooled regressions by product groups

sample	Specification 1				Specification 2			
	regressor	BW	LAPD	PPD	regressor	BW	LAPD	PPD
	log(DISTANCE)	0.003‡	0.012‡	0.014‡	TC	0.006‡	0.011‡	0.011‡
	DISTANCE DUMMY	-0.013‡	-0.016‡	-0.006‡	NTC	0.013‡	0.057‡	0.054‡
Full	WAGE	0.230†	0.959‡	0.785‡	WAGE	0.232†	0.954‡	0.779‡
(0.154)	RENT	0.292‡	1.540‡	1.341‡	RENT	0.289‡	1.516‡	1.326‡
{0.125}	POP DENSITY	-0.019	0.019	0.048‡	POP DENSITY	-0.018	0.027	0.052‡
	SAME STATE	-0.004‡	-0.008‡	-0.002‡	SAME STATE	-0.015‡	-0.009‡	0.001
	Adj-R^2	0.211	0.137	0.258	Adj-R^2	0.211	0.137	0.258
Category 1								
	log(DISTANCE)	0.009*	0.022‡	0.022‡	TC	0.009‡	0.017‡	0.015‡
	DISTANCE DUMMY	-0.020‡	-0.021‡	-0.007	NTC	0.033‡	0.089‡	0.084‡
Perishable	WAGE	0.527*	0.695	0.475‡	WAGE	0.526*	0.686	0.464‡
(0.180)	RENT	0.431‡	0.787‡	0.614‡	RENT	0.422‡	0.755‡	0.591†
{0.119}	POP DENSITY	0.015	0.040*	0.032	POP DENSITY	0.018	0.049‡	0.038
	SAME STATE	-0.004	-0.007*	-0.002	SAME STATE	-0.018*	-0.008	0.006
	Adj-R^2	0.234	0.217	0.252	Adj-R^2	0.234	0.218	0.254
	log(DISTANCE)	0.003*	0.013‡	0.014‡	TC	0.007‡	0.012‡	0.010‡
Non-	DISTANCE DUMMY	-0.016‡	-0.006	0.004	NTC	0.011	0.052‡	0.046‡
perishable	WAGE	0.169	0.553‡	0.462‡	WAGE	0.173	0.549‡	0.457‡
(0.161)	RENT	0.366‡	1.115‡	0.946‡	RENT	0.363‡	1.100‡	0.937‡
{0.095}	POP DENSITY	-0.052	0.016	0.055‡	POP DENSITY	-0.051*	0.021	0.057‡
	SAME STATE	-0.005	-0.005†	0.000	SAME STATE	-0.019‡	0.000	0.009†
	Adj-R^2	0.139	0.164	0.238	Adj-R^2	0.139	0.164	0.238
	log(DISTANCE)	-0.001	0.008‡	0.007‡	TC	-0.004	0.006*	0.008‡
	DISTANCE DUMMY	-0.004	-0.006	-0.016*	NTC	0.003‡	0.046‡	0.035‡
Service	WAGE	0.006	1.112‡	1.488‡	WAGE	0.009	1.106‡	1.486‡
(0.120)	RENT	0.064*	2.782‡	2.548‡	RENT	0.067‡	2.757‡	2.532‡
{0.161}	POP DENSITY	-0.013	0.071	0.055	POP DENSITY	-0.013	0.079	0.059
	SAME STATE	-0.002	-0.007‡	-0.006‡	SAME STATE	-0.007†	0.002	-0.013*
	Adj-R^2	0.150	0.181	0.239	Adj-R^2	0.150	0.181	0.239
Category 2								
	log(DISTANCE)	0.009*	0.022‡	0.025‡	TC	0.009*	0.018‡	0.018‡
Not-	DISTANCE DUMMY	-0.022‡	-0.022*	-0.004	NTC	0.040‡	0.093‡	0.097‡
locally	WAGE	0.449	0.555	0.430‡	WAGE	0.446	0.547	0.418‡
(0.210)	RENT	0.482‡	0.798‡	0.808‡	RENT	0.467‡	0.764‡	0.779†
{0.129}	POP DENSITY	0.017	0.052‡	0.048	POP DENSITY	0.021	0.062‡	0.056
	SAME STATE	-0.005	-0.009*	-0.004	SAME STATE	-0.018	-0.010	0.010
	Adj-R^2	0.121	0.209	0.236	Adj-R^2	0.122	0.210	0.238
	log(DISTANCE)	0.004*	0.015‡	0.015‡	TC	0.008‡	0.013‡	0.011‡
Maybe-	DISTANCE DUMMY	-0.017‡	-0.007*	0.001	NTC	0.012*	0.059‡	0.051‡
locally	WAGE	0.297*	0.746‡	0.572‡	WAGE	0.301	0.742‡	0.566‡
(0.161)	RENT	0.414‡	1.158‡	0.899‡	RENT	0.412‡	1.139‡	0.889‡
{0.100}	POP DENSITY	-0.057	0.012	0.042*	POP DENSITY	-0.056†	0.018	0.045*
	SAME STATE	-0.005	-0.006*	0.001	SAME STATE	-0.021‡	-0.001	0.008
	Adj-R^2	0.148	0.156	0.239	Adj-R^2	0.148	0.156	0.240
	log(DISTANCE)	0.000	0.007‡	0.008‡	TC	-0.003	0.006	0.008*
Locally-	DISTANCE DUMMY	-0.004	-0.009	-0.014*	NTC	0.003*	0.041‡	0.033‡
produced	WAGE	0.029	0.996‡	1.219‡	WAGE	0.033	0.991‡	1.218‡
(0.114)	RENT	0.052*	2.318‡	2.123‡	RENT	0.054*	2.298‡	2.110‡
{0.145}	POP DENSITY	0.000	0.062	0.054	POP DENSITY	0.000	0.068	0.058
	SAME STATE	-0.002	-0.006‡	-0.005‡	SAME STATE	-0.007‡	-0.002	-0.011*
	Adj-R^2	0.151	0.203	0.272	Adj-R^2	0.151	0.203	0.272

NOTES: See eqs.(3)-(4) for regression equations. ‡, †, and * respectively indicate statistical significance at the 1%, 5%, and 10% error levels and robust clustered standard errors are used. The two numbers in the first column are the average values of BW (in parentheses) and LAPD (in curved brackets).

TABLE 6

Time-varying effect of distance on PPD

item	log distance ($\hat{\rho}_0$)	time dummy ($\hat{\rho}_1$)
1	0.024‡	-0.001‡
2	0.011‡	-0.002‡
3	0.028‡	0.004‡
4	0.021‡	-0.003‡
5	0.010‡	-0.001‡
6	0.013‡	-0.008‡
7	0.021‡	-0.003‡
8	0.030‡	0.007‡
9	0.054‡	0.003‡
10	0.014‡	0.002‡
11	0.028‡	0.001‡
12	0.013‡	0.003‡
13	0.027‡	0.008‡
14	0.011‡	0.000
15	0.018‡	-0.006‡
16	0.019‡	0.007‡
17	0.010‡	0.007‡
18	0.010‡	-0.005‡
19	0.026‡	-0.005‡
20	0.017‡	0.000†
21	0.003*	0.013‡
22	0.010‡	-0.002‡
23	0.011‡	0.003‡
24	0.027‡	0.003‡
25	0.027‡	0.004‡
26	0.025‡	-0.005‡
27	0.004‡	0.005‡
28	0.011‡	0.000‡
29	0.009‡	-0.003‡
30	0.023‡	-0.004‡
31	0.001‡	0.005‡
32	0.005‡	0.000
33	0.007‡	0.005‡
34	0.003‡	-0.002‡
35	0.009‡	0.005‡
36	0.006‡	0.006‡
37	0.022‡	-0.003‡
38	-0.005‡	0.010‡
39	0.004‡	0.004‡
40	0.005‡	0.000
41	0.008‡	-0.002‡
42	0.011‡	0.002‡
43	0.006‡	0.003‡
44	0.005‡	-0.004‡
45	0.024‡	0.001‡

NOTES: The regression equation is

$$PPD^k_{ij,t} = \rho^k_0 \log(DIST_{ij}) + \rho^k_1 \log(DIST_{ij}) \cdot D_t + X_t\beta + \varepsilon^k_{ij,t},$$

where $PPD^k_{ij,t}$ denotes the period-average price difference between cities i and j at time t for product k, X_t is the usual vector of additional explanatory variables at time t, and D_t is a time dummy variable which takes the value of one for the period after 1997.

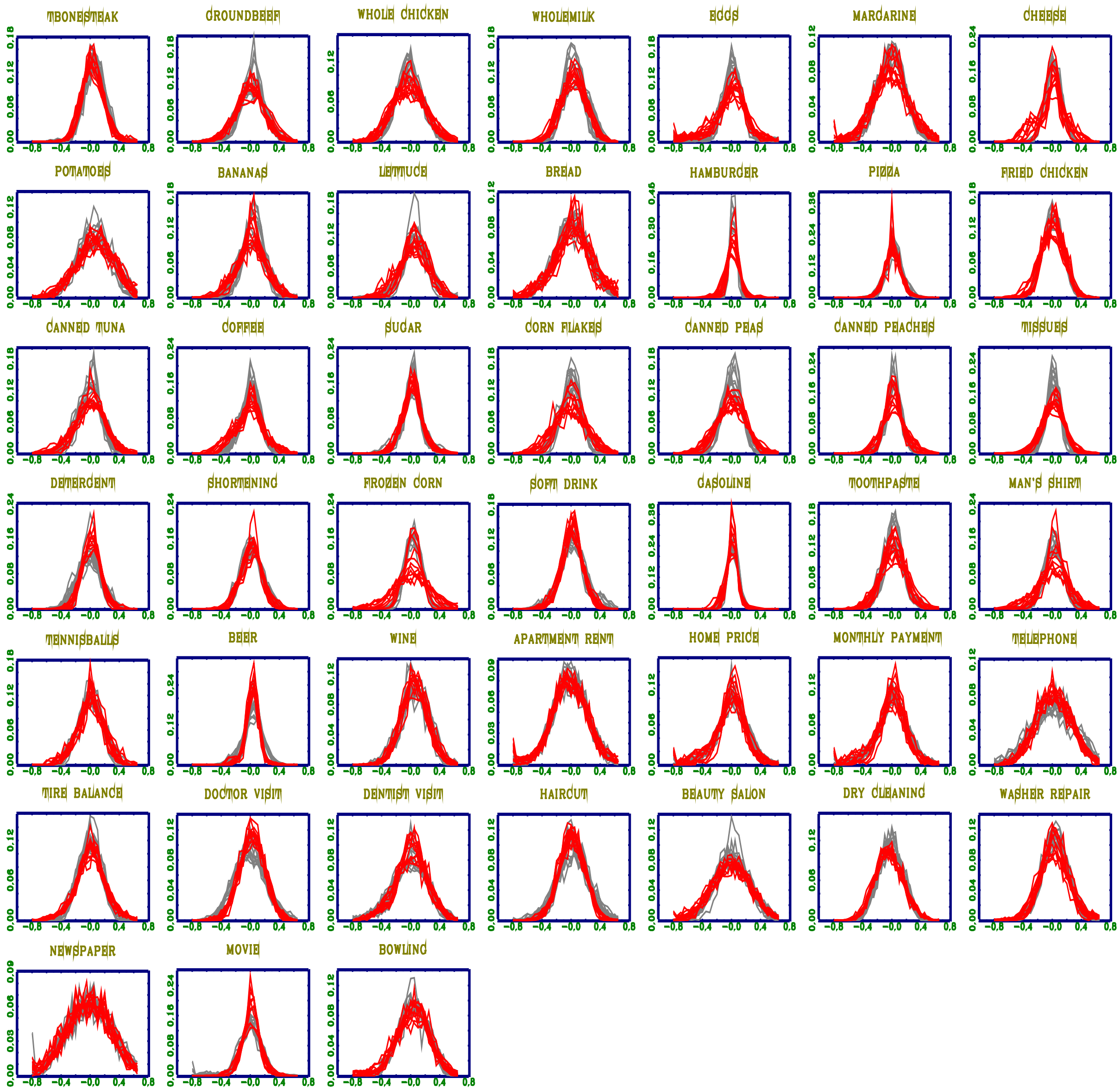


FIGURE 1 Empirical distributions of annual intercity price differentials

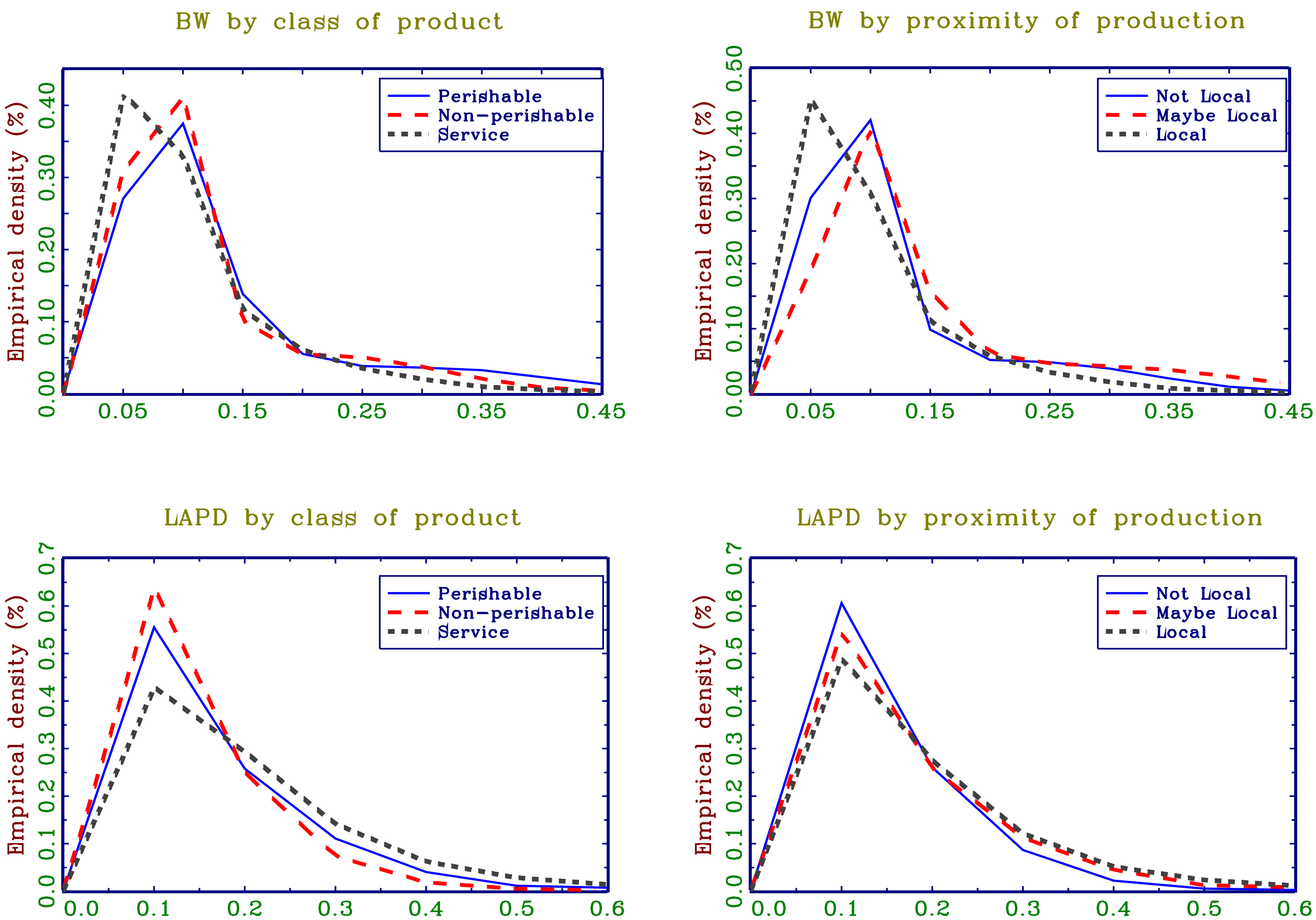
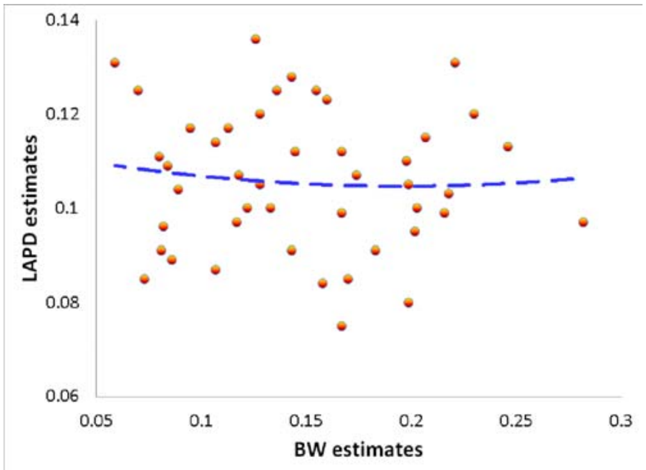


FIGURE 2 Empirical densities of BW and LAPD by product categories



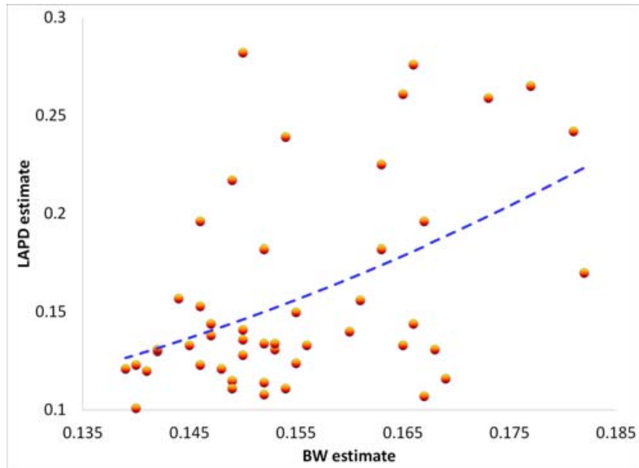


FIGURE 3 Scatterplots of two metrics of market segmentation across products (on the left) and across cities (on the right)

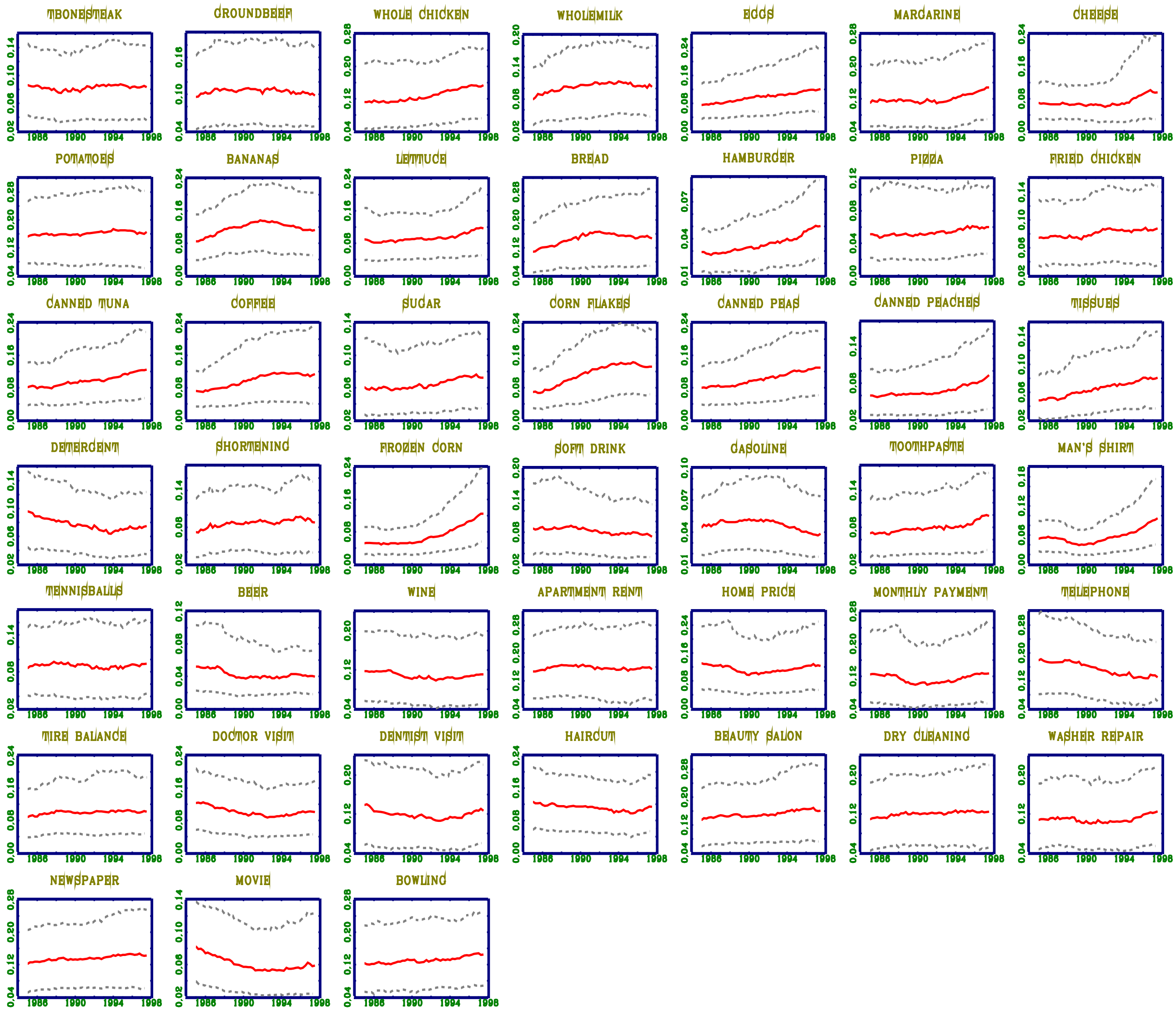


FIGURE 4 Estimated 12-year rolling long term average price differentials (LAPDs) by product

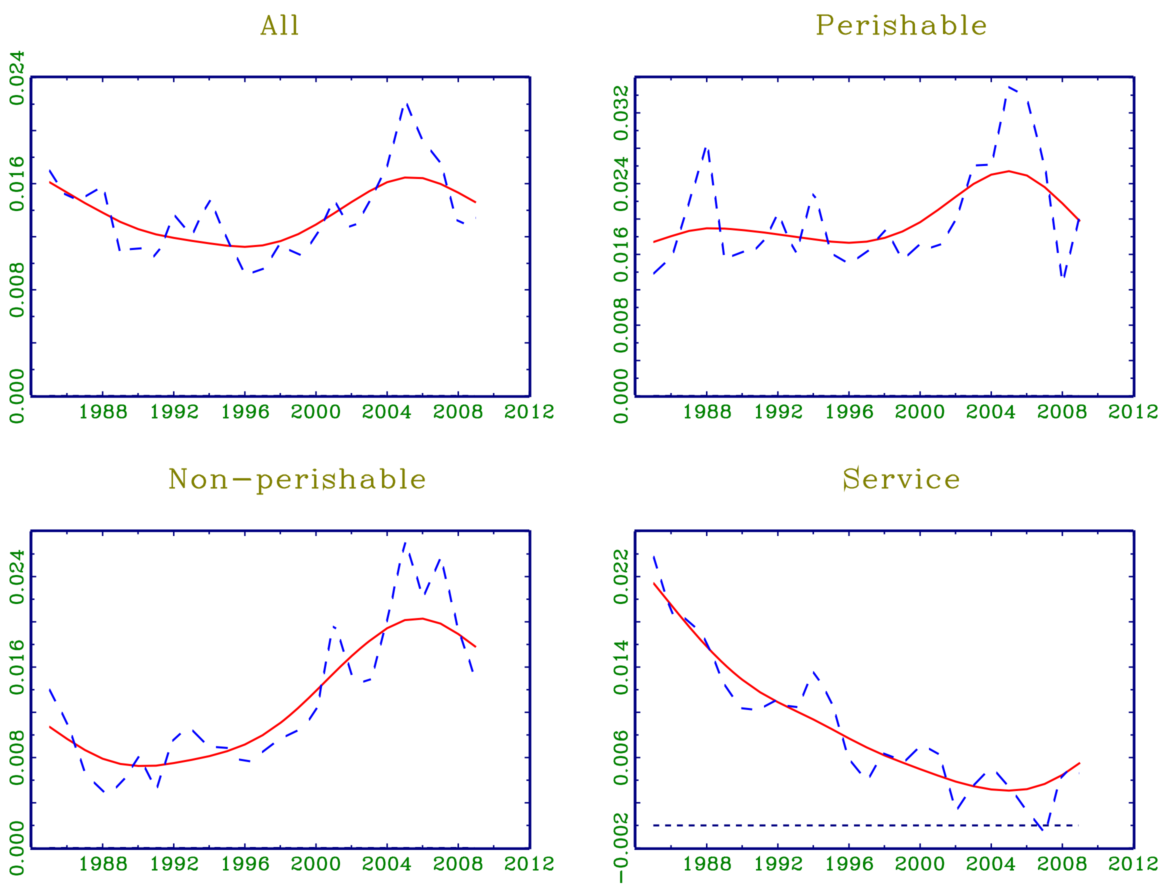


FIGURE 5 Evolution of annualized distance effects on PPD (dotted line) and their HP-filtered values (solid line) by product groups