The Geography of Consumer Prices

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Abstract

We develop a two-country, multi-region dynamic stochastic equilibrium model of relative price determination, in which stores set prices in response to idiosyncratic shocks to productivity. Price adjustment involves a fixed cost. Demand is determined by regionally representative CES-consumers. Due to shopping costs related to distance and the national border, posted prices and prices perceived by consumers may differ. We show that the optimal price is proportional to a weighted average of market prices, with weights negatively related to shopping costs. We apply the model to study how geography determines intra- and international relative prices in a unique panel of store-level consumer prices. We calibrate structural distance and border parameters, and conclude that distance matters a great deal, while the border has a small impact. The implied width of the calibrated border is a tiny fraction of its reduced form counterpart.

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1 Introduction

How does geography, particularly, distance and national borders separating geographical locations apart affect the dynamics of within- and cross-country price differentials? The answer to this question is likely to have profound implications for our understanding of good market segmentation and the behavior of the real exchange rate.[1]

In this project, we combine quantitative theory with store-level measurement to learn about distance and border effects in micro level relative price determination. Our contribution is twofold. First, we develop a discrete time, two-country, multi-region, dynamic stochastic equilibrium model of relative prices. In the model, a large number of heterogeneous stores operate in distinct geographical regions, with each region populated by an infinitely lived, representative consumer equipped with CES-preferences. Consumers bear the cost of shopping in remote stores, resulting in distance- and border-related wedges between prices posted by stores and prices perceived by consumers. Facing geographically diverse demand, in turn, monopolistically competitive stores set prices in response to idiosyncratic shocks to productivity, subject to fixed cost to price adjustment.

As it is standard in models of monopolistic competition, as optimally setting their price, stores care about the average of other stores' prices. In our model, however, it is a *weighted* average of prices that the optimal price depends on, with stores paying more attention to prices set in their vicinity relative to ones set at distance. To highlight the basic mechanism at work, a stylized example with only two regions, A and B, is instructive. Consider first a shock in region A. If the shock is large enough to overcome the cost of price adjustment, stores in region A decide to change their price. Then, relative to consumers in region B, consumers in region A would care more about the change in relative prices in this region, adjusting more their relative demand, as they are located closer to stores in region A. As the demand of stores in region B is mainly determined by consumers in region B who are affected to a lesser extent by the initial change in prices in region A, in turn, these stores care less about the resulting shift in relative demand than stores in region A.

The model is essentially a multi-region variant of Blanchard and Kiyotaki (1987), appended with two additional frictions. First, as in Anderson and van Wincoop (2003), buying across space is costly, with the cost being related to distance and the border. Second, as in Golosov and Lucas (2007), Klenow and Willis (2006), and Midrigan (2011), stores are subject to fixed cost to nominal price adjustment when contemplating to reset the price in response to idiosyncratic shocks to productivity. Both of these modeling assumptions build on well-known ingredients robustly rooted in microeconomic evidence. First, for particular individual products basic descriptive patterns in international pricing indicate pervasive deviations from the Law of One Price (LOP).[2] International price data also show that the volatility of relative price deviations is related both

[1]See Obstfeld and Rogoff (2001).

[2]See Asplund and Friberg (2001), Ghosh and Wolf (1994), and Haskel and Wolf (2001).

to the distance and the border between locations.[3] Furthermore, misalignments in cross-location price differentials are relatively slow to fade away, especially at low levels of product aggregation.[4] While each one of these pieces of evidence has its own limitation, taken together, they do suggest that within- and cross-country price differentials tend *not* to be eliminated, and that geography may influence pricing behavior. Finally, in a distinct strand of literature, drawing on highly disaggregated store-level price data collected in several countries, a number of empirical studies conclusively establish that retail prices are lumpy, staggered, and respond to shocks. These results point to fixed costs and shock heterogeneity as important elements in the price setting process.[5]

Our second contribution in this paper is to apply the quantitative model to identify and pin down the underlying structural distance and border parameters governing relative price dynamics via a moment matching procedure. The point of departure is the seminal paper by Engel and Rogers (1996), estimating a cross-sectional, reduced form regression equation in which log distance, a binary border variable and location-specific dummies explain the time-series volatility of cross-location relative prices in sector-level CPI data for 14 categories of goods in 23 cities in Canada and the US. They find that the distance and border coefficients are both sizable and significant, and that the implied distance equivalent of the border is enormous.[6] These results have been confirmed in a number of subsequent studies using similar data and empirical specifications.[7] In recent work, Gorodnichenko and Tesar (2009) question the identification approach in Engel and Rogers (1996) and conclude that "the border coefficient that emerges from tests comparing within-country prices to cross-border prices tells us little about actual border effects in the absence of a fully articulated structural model or a (natural) experiment". Indeed, the challenge we take up is to confront directly our dynamic, spatial model of price setting to highly disaggregated international price data.

The focus of the data analysis is on cross-location price deviations in a unique panel dataset of retail-level price quotations recorded in two small, neighboring economies, Hungary and Slovakia. Our sample includes price observations of a diverse group of forty-six narrowly defined, very specific consumer good and service items sold in about an average of ninety stores over a period of sixty months. The estimation procedure is directed at matching key temporal and spatial moments in the microeconomic price and distance data with those obtained in the calibrated structural model, including the average frequency and size of individual price changes, along with reduced form distance and border coefficients *a la* Engel and Rogers (1996).

Our results, first, confirm that in reduced form regressions both geographical

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[3]See Engel and Rogers (1996) and Parsley and Wei (2001).

[4]See Obstfeld and Taylor (1997) and Parsley and Wei (1996).

[5]See, for instance, Bils and Klenow (2004), Dhyne *et al* (2006), Gabriel and Reiff (2010), Nakamura and Steinsson (2008) and Wolman (2007).

[6]The estimated width of the border between Canada and the US is 75,000 miles. In Parsley and Wei (2001), the same figure for Japan and the US is 6.5 trillion miles.

[7]In Broda and Weinstein (2008) and Gorodnichenko and Tesar (2009) the border matters much less so than in other related studies.

distance and the border are highly significant, and the implied width of the border is truly giant. At the same time, our structural estimates show that while distance does matter a great deal, the national border adds little extra in explaining store-level relative price dynamics. Indeed, the border effect is negative for a few products in our sample. Overall, the structurally calibrated width of the border is a tiny fraction of the reduced form one. We argue that the structural and the reduced form approaches deliver different results as the former one conditions explicitly on frictions both in the price setting and the commuting process, allowing one to separate the contributions of these two elements, while the estimated reduced form coefficient combines these two effects into a single figure.

The rest of the paper is organized as follows. In Section 2 we describe our model of international pricing, highlighting the propagation mechanism driving the basic results. The dataset used to estimate the distance and border effects is introduced in Section 3. The estimation approach and results are presented in Section 4, while Section 5 concludes.

2 Model

To study how geography impacts on microeconomic pricing decisions, we develop a one-good, two-country, multi-region, dynamic model of price setting. The basic structure builds on Blanchard and Kiyotaki (1987). The model economy is composed of R regions indexed by $r = 1, ..., R$, with a national border splitting these regions into two countries. In each region, there is a representative consumer and a set of single-product stores with measure n_r. The total measure of stores is $\sum_{r=1}^{R} n_r = 1$. Consumers are indexed by $j = 1, ..., R$. Stores are denoted by i, so for instance stores with $0 \leq i \leq n_1$ are in region 1, stores with $n_1 < i \leq n_1 + n_2$ are in region 2, and stores with $n_1 + ... + n_{R-1} < i \leq 1$ are in region R. Conversely, if store i is in region r, we denote that region as $r(i)$. Finally, the share of region r in the aggregate real output, α_r is assumed to be equal to the measure of stores in that region, n_r.

2.1 Geography

We first describe the geographical structure in the model. The idea we build on is that shopping across locations is costly, and that this cost is potentially related to geographical distance and the national border. In particular, we assume that there is an iceberg-type shopping cost, $\tau^j_{r(i)}$, paid by consumer j buying at store i located in region r. The shopping cost creates a wedge between the price the consumer actually pays and the shopping-cost augmented price that is relevant in determining her demand. That is, $P(i)$ posted by a store in region $r(i)$ is perceived as $(1 + \tau^j_{r(i)})P(i)$ by consumer j shopping in that store.

We specify the log of shopping cost as $\log\left(1 + \tau^j_{r(i)}\right) = d \log D\left(r(i), j\right) + bB\left(r(i), j\right)$, where $D\left(r(i), j\right)$ is a continuous variable representing distance between store $r(i)$ and consumer j, and $B(r(i),j)$ is a binary variable taking on a value of one if the two regions $r(i)$ and j are in different countries, and zero if they are in the same country. d is the distance and b is the border parameter. In general, the larger the distance $D(r(i),j)$ between store $r(i)$ and consumer j, the higher the shopping cost $\tau^j_{r(i)}$, implying $d > 0$. Depending on the particular geographical structure and the regional distribution of prices in the two countries, the border coefficient b could in principle take on any value. For instance, if local price differentials regularly switch sign as moving along the border, b may take on a negative value as well.

2.2 Consumers

Consumer j maximizes the expected value of her lifetime utility derived from consuming and working over an infinite horizon as

$$\max_{\left\{C^j_t(i),L^j_t\right\}} E\sum_{t=0}^{\infty}\beta^t u\left(C^j_t, L^j_t\right),$$

where $C^j_t(i)$ is consumption of consumer j in store i at time t. C^j_t is a CES-aggregate with elasticity θ of consumer j's consumption, $C^j_t = \left[\int C^j_t(i)^{\frac{\theta-1}{\theta}}di\right]^{\frac{\theta}{\theta-1}}$. L^j_t is the amount of labor supplied by consumer j at time t in a perfectly flexible manner. The felicity function is specified as $u(C^j_t, L^j_t) = \log(C^j_t) - \mu L^j_t$, where μ is the disutility of labor.

The budget constraint of consumer j is

$$\int (1+\tau^j_{r(i)})P_t(i)C^j_t(i)di = \widetilde{w}_t L^j_t + \widetilde{\Pi}^j_t + T^j_t,$$

where $P_t(i)$ is the price posted by store i at time t, $\widetilde{w}_t$ is the nominal wage rate, $\widetilde{\Pi}^j_t$ is the nominal profit stores return to consumer j owing them at time t, and T^j_t is the amount of government transfer distributed to consumer j at time t. The transfer has two elements: there is a travel-related part that ensures that real output in regions grows at the same rate, so that each region j has a constant share α_j in sectoral output, and there is an element due to growing money supply.

The solution to this optimization problem is standard, giving rise to demand by consumer j in store i as

$$C^j_t(i) = C^j_t\left[\frac{(1+\tau^j_{r(i)})P_t(i)}{P^j_t}\right]^{-\theta},$$

where P^j_t is a CES-aggregate of prices perceived by consumer j, defined as

$$P^j_t = \left[\int [(1+\tau^j_{r(i)})P_t(i)]^{1-\theta}di\right]^{\frac{1}{1-\theta}}.$$

This result shows that the demand of consumer j at store i relative to her total demand depends on relative perceived prices, i.e. the prices she perceives at particular stores relative to the average of her perceived prices.

2.3 Stores

The single-product stores operate in a monopolistically competitive market. The nominal profit of store i is defined as

$$\widetilde{\Pi}_t(i) = P_t(i)Y_t(i) - \widetilde{w}_t L_t(i),$$

where $Y_t(i)$ is the amount of final good store i sells at price $P_t(i)$. The store uses a single labor input, $L_t(i)$ to produce its output, $Y_t(i)$. There are two stochastic shocks affecting stores' decisions. $A_t(i)$ is an idiosyncratic productivity shock specific to store i, while Z_t is a shock common to all stores. The production function of store i is thus

$$Y_t(i) = Z_t A_t(i) L_t(i)^{\eta},$$

where η is the returns-to-scale parameter. Sectoral productivity is growing at a stochastic rate $g_{Z,t+1} = \log Z_{t+1} - \log Z_t$,[8] with the growth rate being an AR(1) process around its mean, μ_{gZ}, defined as

$$[g_{Z,t+1} - \mu_{gZ}] = \rho_Z [g_{Z,t} - \mu_{gZ}] + \varepsilon_{Z,t+1}.$$

Idiosyncratic productivity also follows an AR(1) process with the persistence parameter ρ_A,

$$\log A_{t+1}(i) = \rho_A \log A_t(i) + \varepsilon_{A,t+1}.$$

The store meets demand by adjusting its perfectly flexible labor input, therefore labor demand is

$$L_t(i) = \left[\frac{Y_t(i)}{Z_t A_t(i)}\right]^{\frac{1}{\eta}}.$$

Market clearing implies $Y_t(i) = C_t(i)$. Total demand for store i, $Y_t(i)$, is thus defined through

$$Y_t(i) = \left[\sum_{j=1}^{R} C_t^j(i)^{\frac{\theta-1}{\theta}}\right]^{\frac{\theta}{\theta-1}} = \left[\sum_{j=1}^{R} C_t^{j\,\frac{\theta-1}{\theta}} \left(\frac{(1+\tau^j_{r(i)})P_t(i)}{P_t^j}\right)^{1-\theta}\right]^{\frac{\theta}{\theta-1}},$$

where $C_t^j(i)$ are optimal demands by consumers $j = 1, \ldots, R$. Using the result that the share of each region in sectoral consumption corresponds to the share of stores operating in that region, that is, $C_t^j = \alpha_j C_t$ for all j, we write

$$Y_t(i) = P_t(i)^{-\theta} C_t \overline{P}_i(t)^{\theta} = C_t \left[\frac{P_t(i)}{\overline{P}_t(i)}\right]^{-\theta},$$

[8] In our quantitative work, we make aggregate productivity deterministic by shutting down its variance to zero.

where $\overline{P}_t(i)$ is the relevant price aggregate for store i; i.e. the expenditure share weighted CES-average of perceived prices of consumers shopping at store i, defined as

$$\overline{P}_t(i) = \left[\sum_{j=1}^{R} \alpha_j^{\frac{\theta-1}{\theta}} \left(\frac{P_t^j}{1+\tau_{r(i)}^j}\right)^{\theta-1}\right]^{\frac{1}{\theta-1}}.$$

Since nominal output is assumed to grow at an exogenously given rate g_{PY}, and real output is growing at the stochastic rate g_Z, the inflation rate will fluctuate around $g - \mu_{gZ}$, with its exact value depending on the realization of $g_{Z,t}$. Now we write the stationary profit function for store i by normalizing the nominal profit by the per-store nominal output, $\overline{P}_t(i)C_t$, as

$$\begin{aligned} \Pi_t(i) &= \frac{P_t(i)Y_t(i)}{\overline{P}_t(i)C_t} - \frac{\widetilde{w}_t}{\overline{P}_t(i)C_t}\left[\frac{Y_t(i)}{Z_tA_t(i)}\right]^{\frac{1}{\eta}} = \\ &= \left[\frac{P_t(i)}{\overline{P}_t(i)}\right]^{1-\theta} - w_t\left[\frac{C_t}{Z_tA_t(i)}\right]^{\frac{1}{\eta}}\left[\frac{P_t(i)}{\overline{P}_t(i)}\right]^{-\frac{\theta}{\eta}}. \end{aligned}$$

In this formula $w_t = \frac{\widetilde{w}_t}{\overline{P}_t(i)C_t}$ stands for the stationary normalized wage. Denoting the relative price $\frac{P_t(i)}{\overline{P}_t(i)}$ by $p_t(i)$, and the "aggregate cost factor" $w_t\left[\frac{C_t}{Z_t}\right]^{\frac{1}{\eta}}$ by ζ_t, the stationary profit function of store i simplifies to

$$\Pi_t(i) = p_t(i)^{1-\theta} - p_t(i)^{-\frac{\theta}{\eta}}A_t(i)^{-\frac{1}{\eta}}\zeta_t.$$

2.4 Solution

Given demand, dropping time indices, store i sets the nominal price $P(i)$ in every period to maximize the expected present value of its profit. The optimal price setting decision is a stochastic, dynamic decision problem. The state in general comprises of the relative price of the store at the beginning of the current period, $p(i)$, the growth rate of sectoral technology, g_Z, the inflation rate, π, the aggregate cost factor, ζ, the idiosyncratic productivity, $A(i)$, and the distribution of firms over their idiosyncratic state variables, Ω. The control is the relative price set by the store. In each period, given the state, stores evaluate the gains from changing the nominal price in terms of additional expected profits relative to the fixed cost of the price change, taking into account the expected change in the value of the dynamic program with and without the price change. Formally, denoting the next period realization of any current variable x by x', the value of the dynamic decision problem is

$$\begin{aligned} & V(p(i), A(i), g_Z, \pi, \zeta, \Omega) \\ = & \max_{C,NC}\left\{V^C(A(i), g_Z, \pi, \zeta, \Omega), V^{NC}(p(i), A(i), g_Z, \pi, \zeta, \Omega)\right\}. \end{aligned}$$

In particular, if the store decides to change its current relative price from p to p', it does so by maximizing the value function

$$\begin{aligned} & V^{C}(A(i), g_Z, \pi, \zeta, \Omega) \\ = \quad & \max_{p'(i)} \left\{ \Pi(p'(i), A(i), \zeta) - \psi + \beta E_{A'(i),\zeta'|A(i),\zeta} V(p'(i), A'(i), g'_Z, \pi', \zeta', \Omega') \right\}. \end{aligned}$$

where ψ is the real cost of changing the price. Alternatively, if the store does not change its relative price, then its current relative price depreciates by the inflation rate, π. In this case, the value of the dynamic programming problem is

$$\begin{aligned} & V^{NC}(p(i), A(i), g_Z, \pi, \zeta, \Omega) \\ = \quad & \Pi\left(\frac{p(i)}{1+\pi}, A(i), \zeta\right) + \beta E_{A'(i),\zeta'|A(i),\zeta} V\left(\frac{p(i)}{1+\pi}, A'(i), g'_Z, \pi', \zeta', \Omega'\right). \end{aligned}$$

In sum, equilibrium conditions in the model are the following: consumers maximize their lifetime expected utility under the budget constraint, taking prices and wages as given, stores solve their dynamic optimization problem, product markets clear with $Y_t(i) = C_t(i)$, and nominal output grows at the constant rate, g_{PY}.

We solve the dynamic optimization problem numerically. We assume that the standard deviation of the aggregate productivity shock innovation, $\sigma_Z = 0$, so that $g_{Z,t} = \mu_{gZ}$ for all t. This, together with the constant nominal growth assumption, implies no aggregate uncertainty, hence aggregate state variables are equal to their steady-state values. In particular, $g_{Z,t} = \mu_{gZ}$ and $\pi_t = g_{PY} - \mu_{gZ}$ for all t. The other two aggregate state variables, ζ_t and Ω_t (the aggregate cost factor and the distribution of firms) are also time-invariant, but in the absence of a closed-form solution, we calculate their steady-state values numerically.

For this, we apply the following iterative procedure. The first step is to make an initial guess for the steady-state aggregate cost factor, ζ_0. In practice, this amounts to selecting the solution to the flexible-price problem as the initial value (see Appendix A). Given this guess and the steady-state inflation rate, $\pi = g_{PY} - \mu_{gZ}$, we find the value function and the corresponding policy function by value-function iteration, using a fine grid over individual relative prices and idiosyncratic productivities. Then, based on the policy function and the law of motion of the idiosyncratic productivity shock $A(i)$, we find the steady-state distribution of firms over this grid.[9] Finally, we check the sign of the average relative price in the resulting steady-state distribution: if it is positive (negative), then we decrease (increase) our initial guess for the aggregate cost factor ζ so that firms set lower (higher) relative prices on average. We do this iteration in ζ until the average relative price in the resulting steady-state distribution is exactly zero.

[9] To do this, we start from the two-dimensional uniform distribution, and apply the successive price adjustments (based on the policy function) and idiosyncratic productivity innovations (based on the true law of motion) until the distribution converges.

2.5 Model Analytics

The key insight in the mechanics of the model is that when stores set the price, they care about other stores' prices, especially about ones in nearby areas. Formally, geographical location is part of the state determining the choice of nominal price at say store i, as it impacts on the relative price, $p_t(i)$, through the shopping cost matrix entering the definition of the average perceived price at the particular store i, $\overline{P}_t(i)$.

The more detailed argument on how geography matters in microeconomic pricing decision proceeds in two stages. Throughout, we make the standard assumption that the elasticity of substitution exceeds unity, $\theta > 1$. First, consider a shock to productivity in store k, with say $A(k)$ falling. If the shock is large enough to overcome the fixed cost of price adjustment, store k decides to raise its price. The next question is: how does the new, higher price in store k affect the representative consumer in region j? The answer is implicit in the partial derivative of the average perceived price of consumer j, P_t^j, with respect to the price set in store k, $P_t(k)$,

$$\frac{\partial P_t^j}{\partial P_t(k)} = \left(\frac{P_t^j}{P_t(k)}\right)^{\theta} \frac{1}{\left(1+\tau_{r(k)}^j\right)^{\theta-1}} > 0.$$

The positive sign of this derivative means that the representative consumer in region j faces a higher perceived price. In addition, the derivative is decreasing in $\tau_{r(k)}^j$, implying that the more consumers need to travel to a particular store to shop there, the less their average perceived price is affected by the initial price change.

Finally, to understand why a productivity shock at store k affects pricing decisions at another store, say store l, recall that the price aggregate in store l, $\overline{P}_t(l)$, defining the relative price $p_t(l) = \frac{P_t(l)}{\overline{P}_t(l)}$ is a weighted average of the perceived prices of consumers shopping at this store. The change in this price aggregate in response to a change in $P_t(k)$ then obtains as

$$\frac{\partial \overline{P}_t(l)}{\partial P_t(k)} = \sum_{j=1}^{R} \frac{\alpha_j^{\frac{\theta-1}{\theta}} \left(\frac{P_t^j}{P_t(k)}\right)^{\theta} \left(\frac{P_t^j}{\overline{P}_t(l)}\right)^{\theta-2}}{\left[\left(1+\tau_{r(l)}^j\right)\left(1+\tau_{r(k)}^j\right)\right]^{\theta-1}} > 0.$$

That is, the average price rises in response to the shock. The result also shows that in general, the response is smaller, the larger the distance between stores l and k, with nearby consumers having a larger weight in the average price entering the relative price of store l. Consequently, store l cares less about the resulting shift in relative demand, the farther away it is from store k experiencing the initial shock to productivity.

3 Data

We apply the structural model developed above to a unique, monthly frequency panel of store-level consumer prices. The data are originally collected for calculating consumer price indices in two small, open economies sharing a national border, Hungary and Slovakia. The baseline sample includes a diverse group of 46 very narrowly defined, specific goods and services, falling into 6 subgroups as shown in Table 1.[10]

The items we consider are extracted from the universe of several hundred items observed in the two countries (896 in Hungary and 703 in Slovakia), based on the exclusion criteria that the items actually observed in both countries are similar. This leaves 191 items in the broader sample. We then apply a second filter requiring that the physical attributes of particular goods or services are identical within and across countries, delivering a final sample of 46 items.[11] In terms of coverage, our final sample contains about 7.1% of the entire Hungarian CPI basket in 2006.

Table 1: Data summary - Items by CPI categories

CPI category	**Number of products**	**CPI weight (HU 2006)**
Unprocessed food	15	2.228
Processed food	11	1.328
Clothes	1	0.039
Non-energy industrial goods	13	0.610
Energy (oil) products	2	2.373
Services	4	0.549
TOTAL	**46**	**7.127**

We also drop price observations from regions that are away from the Hungary-Slovakia border and thus are likely to have negligible impact on patterns in cross-border shopping. The resulting final sample consists of prices observed in 6 Hungarian counties (out of 20 in the whole country) with 35 cities and 5 Slovakian counties (out of 8 in the whole country) with 23 cities. Our preferred measure of distance between the selected locations is in minutes of the quickest route as reported at www.viamichelin.com as of April 2008.[12] The map in Figure 1 indicates how we zoom on regions along the border.

For the average product in our sample, prices are observed in about a total of 90 distinct retail stores per month,[13] and over a 60-month time-span between January 2002 through December 2006. The final sample comprises of a total

[10]Table 5 in the Appendix lists all 46 items in the sample.

[11]Initially, we selected 48 items to this final, narrow sample but we dropped 2 of them (A4-size drawing papers and Scissors) as the model could not be calibrated to the empirical moments.

[12]As there was no major road construction works between 2006 and 2008 in this area, the 2008 data should be a good approximation of true distances in our sample period

[13]There are about 170 stores on average in the full sample, when we include all counties in

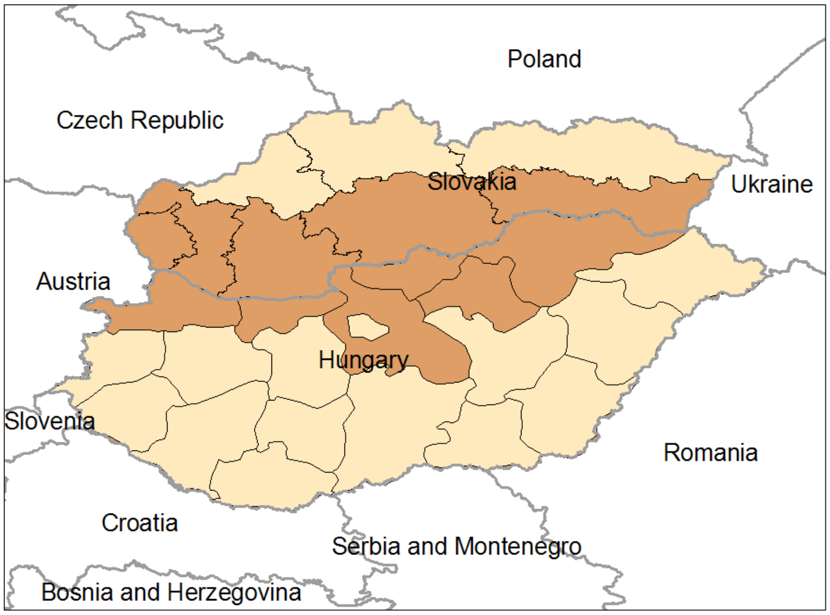

Figure 1: Regions in Hungary and Slovakia

of about 260,000 individual price observations. We perform two standard data corrections in this sample. First, we replace all imputed prices, i.e. when the price is not observed for some reason and a statistical procedure is used to generate an "artificial"price quote, with the last normal price observation. Second, we filter out all sales-related price changes.[14]

We believe that this dataset serves as a particularly attractive environment to analyze the border effect. The reason is that nationalities live mixed in the area, people routinely commute for work from one country to the other and there are numerous cross-border family relationships as well, with Hungarian minorities living in the south of Slovakia and also (although to a smaller extent) Slovakians in north-Hungary. Discrepancies in language and culture are thus unlikely to be a major source of border frictions.

the two countries. The retail stores are mostly independent ones in the sense that they do not belong to a hypermarket chain.

[14]The number of imputed and sales-filtered observations are XXX and YYY in the whole sample.

4 Results

4.1 Data Moments

As a point of departure, first, we document averages of relative price variations, both within and across countries, measured as time-series standard deviations in product-level relative prices. The figures we report in Table 2 and Table 6 in the Appendix are simple unweighted averages of relative price standard deviations calculated between all possible pairs of stores within and across countries.[15] Even though the stores we observe are relatively close to each other, much closer than the Canadian and US cities examined in Engel and Rogers (1996) or Japanese and US cities in Parsley and Wei (2001), we see substantial temporal variation in relative prices. The cross-product median standard deviation is 13.1% and 16.1% in Slovakia and Hungary, respectively, and it is 16.3% between the two countries. When we calculate the average time series standard deviation of *changes* in relative prices, the median figure is 8.1% and 8.6% within Slovakia and Hungary, and 8.8% across the border. For the same statistics, Engel and Rogers (1996) find smaller dispersion in Canadian-US *price indices* (1.63% and 3.21% within countries, 3.67% across countries), while Parsey and Wei (2001) report much larger dispersion for Japan and the US (15.85% and 11.56% within countries, and 22.19% across the border).

Table 2: Relative Price Standard Deviations

	Relative prices			Changes in relative prices		
	SK-SK	**HU-HU**	**SK-HU**	**SK-SK**	**HU-HU**	**SK-HU**
Median	0.131	0.161	0.163	0.081	0.086	0.088
1st quartile	0.096	0.105	0.122	0.059	0.065	0.066
3rd quartile	0.173	0.194	0.206	0.100	0.113	0.118

The product-level statistics show that cross-border relative price deviations are in general (for 29 of the 46 products) higher. Gorodnichenko and Tesar (2009) argue that the cross-country measure picks up heterogeneity between countries, including one stemming from exchange rate volatility. To control for this effect, we thus use standard deviations in *relative real prices* in the rest of the empirical analysis. In particular, following Engel and Rogers (1996), we define the relative real price as the log of $(P_g/P)/(P_g^*/P^*)$ where P_g and P_g^* are the nominal price of good g in two particular stores in Hungary and Slovakia, respectively, P and P^* are the aggregate price levels in the two countries, and P_g/P and P_g^*/P^* are the corresponding real prices. With the relative real price, the cross-border median relative price standard deviation changes from 16.3% to 16.2% (or for *changes* in the relative price, from 8.8% to 8.6%). Moreover, product-level figures show that after the exchange rate filtering, the cross-border relative price variation is still larger than variation in any of the two countries

[15] Throughout the paper, we report only the cross-product quartile figures, leaving the detailed product-level results presented in the Appendix.

for 28 products of 46. In this sense, nominal exchange rate variation does not seem to account for the higher cross-border relative price variability.

Another standard explanation for the excess volatility in cross-border relative prices is the relatively large average distance between cross-border locations. To account for this effect, we estimate the reduced form regressions equation introduced in Engel and Rogers (1996) for the full cross-section of store-pairs in our sample. The regression relates the relative price variation between stores to log distance and a border dummy as

$$V(P_{j,k}) = dummies + \beta_D log(D_{j,k}) + \beta_B B_{j,k} + u_{j,k},$$

where $D_{j,k}$ is the geographical distance between the location of stores j and k, and $B_{j,k}$ is a dummy variable representing the presence or absence of the border between stores j and k. Driven by Gorodnichenko and Tesar (2009), the specification includes city and country dummies. The cross-product quartiles of estimated parameters are shown in columns 4 and 5 of Table 3 (Table 7 in the Appendix contains the product-level results). The median distance- and border regression coefficients are $19.2 * 10^{-4}$ and $13.81 * 10^{-3}$, when distance is measured in driving minutes. When distance is measured in kilometers, we obtain similar results, the median distance and border coefficients are $17.3*10^{-4}$ and $13.94*10^{-3}$, respectively. These figures are fairly close to previous estimates using the same estimation framework.[16]

Table 3: Data Moments

	frequency	*size*	$\beta_D * 10^4$	$\beta_B * 10^3$	$e^{\beta_B/\beta_D} - 1$
Median	0.256	0.095	19.20	13.81	4,236
1st quartile	0.166	0.077	13.81	4.22	14
3rd quartile	0.470	0.117	28.63	29.14	$4 * 10^5$

We now turn to calculating the implied width of the border. In distance equivalent terms, it is defined as the extra distance one would have to travel in a country to have the same relative price variation as the one implied by crossing the border while traveling to the same initial distance. Formally, the border width is the solution to the equation, $\beta_D \ln(D + W) = \beta_D \ln D + \beta_B$, so that $W = e^{\beta_B/\beta_D - 1}$ under the assumption of $D = 1$. The last column in Table 3 reports the median reduced form border width estimates (for the product-level estimates, see Table 7 in the Appendix). The median width of the border evaluated at the distance of 1 minute is 4,236. In general, crossing the border is equivalent to adding a multiplicative factor of 4,236 to the distance at which the border effect is evaluated. (If distance is measured in kilometers, the width of the border is 12,763.) This factor of proportionality is somewhat smaller than the similar factor of 75,000 estimated in Engel and Rogers (1996), and much

[16]The baseline estimates in Engel and Rogers (1996) are $10.6 * 10^{-4}$ and $11.9 * 10^{-3}$. In Parsley and Wei (2001) they are $22 * 10^{-4}$ and $64.9 * 10^{-3}$, while in Broda and Weinstein (2008) $47 * 10^{-4}$ and $31.2 * 10^{-3}$. All of these studies measure distance in miles.

smaller than the corresponding figure of 6.5 trillion in Parsley and Wei (2001). These differences may stem from the fact that cross-border distances in our dataset are small, while the level of disaggregation and product homogeneity are high relative to these other data. At the same time, our estimates exceed those of 720 or 328, depending on the specification in Broda and Weinstein (2008), obtained in a sample of retail prices of bar-code level disaggregated, extremely homogenous products. Taken together, the data indicate sizeable, sometimes giant borders effects obtained in the reduced form regression framework.

4.2 Model Calibration

The huge width of the reduced form border may reflect the impact of omitted variables. Since Engel and Rogers (1996), some of these omitted elements in the measured border effect are associated with lumpy and staggered price setting. We thus ask the question: what portion of the reduced form border estimates can be accounted for by the underlying border and distance frictions, relative to plausible frictions in the price setting process, when all of these frictions are jointly placed in a structural model of price setting. To answer this question, by matching four key moments in the model and the data, separately for each individual product, we calibrate the relevant structural parameters in our dynamic, spatial theory of price setting.

We calibrate the model at the monthly frequency, separately for each individual product. For all calibrations, we fix some model parameters that we believe are not essential in matching the moments we target. In particular, we set the discount factor at $\beta = 0.96^{1/12} = 0.9966$, which is consistent with an annual discount factor of 0.96. We also set the elasticity of substitution parameter at $\theta = 5$, implying a 25% markup for monopolistically competitive stores. The growth rate of nominal output is fixed at $g_{PY} = 0.0075$, which is consistent with an annual growth of 9%, approximating well the actual figure both in Hungary and Slovakia during the 2002-2006 period. We also fix the monthly productivity growth rate at $g_Z = 0.0025$, implying an annual growth rate of 3% and inflation rate of 6%, with these figures matching the average inflation and real growth rate in Hungary and Slovakia in the sample period. For simplicity, we also assume that the persistence in the idiosyncratic technology shock process is $\rho_A = 0.5$, a figure close to the one of 0.45 in Golosov and Lucas (2007), 0.66 in Nakamura and Steinsson (2008), and 0.678 in Klenow and Willis (2006). Finally, we also set the returns-to-scale parameter at unity ($\eta = 1$), implying a constant returns-to-scale technology.

We calibrate the remaining four structural parameters, e.g. the menu cost (ϕ), the idiosyncratic shock standard deviation (σ_A), and the structural distance (d) and border (b) parameters to hit two unconditional, the average frequency and absolute size of price changes, and two conditional, the border and distance coefficients in the Engel and Rogers (1996) regression specification, data moments. The median values of all of these data moments are reported in Table 3, while product-level estimates are listed in Table 7 of the Appendix. The menu cost parameter and the idiosyncratic shock standard deviation primarily

Table 4: Structural Parameters

	ψ	σ_A	d	b	$e^{b/d}-1$	60^{-d}
Median	0.0152	0.059	0.174	0.71	89	0.49
1st quartile	0.0069	0.049	0.146	0.52	14	0.44
3rd quartile	0.0205	0.069	0.202	0.93	420	0.55

determine the average frequency and absolute size of price changes,[17] but they do not influence the reduced form regression parameters. In turn, the structural distance and border parameters allow us to match the reduced form distance and border coefficients, but they are less instrumental in hitting the frequency and size of price changes.

The three quartiles of the calibrated structural parameters are reported in columns 2 to 5 of Table 4 (the calibrated parameters for the 46 products are in Table 8 of the Appendix). The median menu cost parameter, calculated as the median menu cost multiplied by the median frequency of price adjustment, is 0.0152. This implies that firms spend about 0.39% of their revenues to adjust prices, a figure close to the estimate of 0.5% reported in Golosov and Lucas (2007). The median idiosyncratic shock standard deviation is about 5.9%. The median calibrated structural distance parameter is 0.174, quite robustly across products, with a relatively narrow interquartile range of [0.146; 0.202]). To explore the economic importance of this parameter, in column 7 of Table 4 we calculate the price discount at which a 60 minute travel time becomes attractive for the representative consumer, 60^{-d}.[18] This calculation shows that, due to distance-related transaction costs the consumer needs as much as a 51% discount to travel to a location 60 minutes away for the median product. Note that the interquartile range of this estimated discount figure is again relatively tight, [0.45; 0.56].

The calibrated structural border parameter is somewhat more dispersed across products; its median value is 0.71, with an interquartile range of [0.52;0.93]. In column 6 of Table 4, we calculate the distance equivalent of the border, $(e^{d/b}-1)$, now based on the calibrated structural parameters. The median figure here is 89; that is, passing the border increases the distance perceived by consumers by a factor of 89. While this figure is still sizeable,[19] it is only about 2 percent of what we estimated in the reduced form regression. The interquartile range of the width is [14;420], much tighter than the reduced-form range of $[14; 4 * 10^5]$. Apparently, the reduced-form approach overstates the border

[17] Increasing ϕ, the frequency decreases and the size increases, while increasing σ_A, both the frequency and the average size increase.

[18] If P_1 is the price at a location 60 minutes away, and P_2 is the price in the current location, then the perceived price 60 minutes away is $(1+\tau)P_1 = 60^d P_1$. The consumer will prefer shopping here if $60^d P_1 < P_2$, i.e. $\frac{P_1}{P_2} < 60^{-d}$.

[19] In our data, the average distance between locations is 155 minutes, so the border adds 155*89=13,795 minutes, or about 230 hours to the distance between stores at this distance. Of course, this figure would be smaller if we calculated trade-weighted average distances. The relevant disaggregated trade data are not available, however.

width, especially for products with a relatively wide underlying border.

5 Conclusions

In concluding their seminal paper, Engel and Rogers (1996) note: "We have found that the distance between markets influences prices, suggesting that price setters take into account prices of nearby competitors. It is probably not too far-fetched to infer that firms would respond more to changes in prices of near substitutes, whether the nearness is in geographical or product space. A reasonable model of price stickiness must take into account how isolated the market is for the product of the price setter. There appears to be a potential for a marriage of the new-Keynesian literature on menu costs and the new trade theory emphasizing the role of geography. "This is exactly the challenge we take up in the current project.

We bring new, dynamic theory and new, store-level data to study how geography affects microeconomic pricing behavior. The dynamic, stochastic theory of spatial price setting we develop combines elements of the menu cost model of Golosov and Lucas (2007) with insights from the gravity model of Anderson and van Wincoop (2003). The main ingredients in the multi-region, two-country menu cost model model include (i) store heterogeneity within and across regions, (ii) representative consumer in each region, and (iii) costly shopping across regions and the border. We show that in this model the optimal price for an individual store depends on a weighted average of all prices, with the weights reflecting the proximity of other stores.

Calibrating the model to conditional and unconditional moments in store level price data, we find that distance matters a great deal, while the border adds relatively little extra to explain the dynamics in spatial price differentials. Compared to the corresponding reduced form estimate, the implied width of the border is tiny. We argue that the reduced form border coefficient confounds the underlying border friction with the effect of lumpy and staggered microeconomic price setting, perhaps along other, unobserved determinants.

The analysis in this paper has a number of obvious limitations. First, while the border effect we quantify is purged from the influence of staggered and lumpy price setting, its structural form remains a black box with no clear interpretation of its primitives. Second, as it assumes shocks common to stores within and across countries away, the model is not tailored to study the impact of uniform (say, global) or differentiated (such as bilateral exchange rate) aggregate shocks on price differentials. Third, more specifically, in calibrating the model, we assume that the persistence of the productivity process is constant and preset. One could think of bringing in further information from other data moments to have this model parameter calibrated as well. Finally, it would be desirable to expand the geographical and product coverage of our data. We plan to address these challenges in future work.

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A Appendix: Flexible Price Solution

If stores can change their price freely, they reset it in every period to maximize current-period profits. In this case, the optimal relative price in store i is

$$p_i^*(t) = \left[\frac{\theta\zeta(t)}{(\theta-1)\eta}\right]^{\frac{\eta}{\theta+\eta-\theta\eta}} A_i(t)^{\frac{-1}{\theta+\eta-\theta\eta}},$$

and the corresponding optimal consumption, relative to per-store output is

$$\frac{C_i^*(t)}{C(t)/n} = \left[\frac{\theta\zeta(t)}{(\theta-1)\eta}\right]^{\frac{-\theta\eta}{\theta+\eta-\theta\eta}} A_i(t)^{\frac{\theta}{\theta+\eta-\theta\eta}},$$

with $\zeta_t = w_t \frac{C_t}{Z_t}$, and $w_t = \frac{\widetilde{w}_t}{P_t C_t}$ being the normalized nominal wage. CES-aggregation of consumption at store i, $C_i^*(t)$ gives $\frac{C^*(t)}{n} = \left[\frac{\sum_{i=1}^n C_i^*(t)^{\frac{\theta-1}{\theta}}}{n}\right]^{\frac{\theta}{\theta-1}}$, which can be rearranged as

$$\frac{\theta\zeta(t)}{(\theta-1)\eta} = \left[\frac{\sum_{i=1}^n \left[A_i(t)^{1/\eta}\right]^{\frac{-\eta+\theta\eta}{\theta+\eta-\theta\eta}}}{n}\right]^{\frac{\theta+\eta-\theta\eta}{-\eta+\theta\eta}},$$

where the expression on the right-hand-side is the CES-average of individual all $A_i(t)^{1/\eta}$ $\frac{\theta\zeta(t)}{(\theta-1)\eta} = \overline{A(t)^{1/\eta}}$. Substituting this into the optimal relative price equation, we obtain

$$p_i^*(t) = \left[\frac{A_i(t)^{1/\eta}}{\overline{A(t)^{1/\eta}}}\right]^{\frac{-\eta}{\theta+\eta-\theta\eta}}.$$

Also, relative output is obtained as

$$\frac{C_i^*(t)}{C(t)/n} = \left[\frac{A_i(t)^{1/\eta}}{\overline{A(t)^{1/\eta}}}\right]^{\frac{\theta\eta}{\theta+\eta-\theta\eta}}.$$

These show that both individually optimal relative prices and relative consumption depend on relative productivities.

Returning to the aggregation equation $\frac{\theta\zeta(t)}{(\theta-1)\eta} = \overline{A(t)^{1/\eta}}$, $\zeta(t) = w(t)\left[\frac{C(t)}{nZ(t)}\right]^{\frac{1}{\eta}}$ can be expressed as $\frac{(\theta-1)\eta}{\theta}\overline{A(t)^{1/\eta}}$. We then normalize the model so that the constant normalized wage w is equal to the expected value of $\frac{(\theta-1)\eta}{\theta}\overline{A(t)^{1/\eta}}$, and hence the term $\left[\frac{C(t)}{nZ(t)}\right]^{\frac{1}{\eta}}$ fluctuates around unity, with the exact value depending on $\overline{A(t)^{1/\eta}}$ relative to its expected value.

Finally, from the aggregation equation $\frac{\theta\zeta(t)}{(\theta-1)\eta} = \overline{A(t)^{1/\eta}}$, we express $\zeta(t) = w(t)\left[\frac{C(t)}{nZ(t)}\right]^{\frac{1}{\eta}}$ as

$$w(t)\left[\frac{C(t)}{nZ(t)}\right]^{\frac{1}{\eta}} = \frac{(\theta-1)\eta}{\theta}\overline{A(t)^{1/\eta}},$$

and hence the total real consumption is

$$C(t) = nZ(t)\left[\frac{(\theta-1)\eta}{\theta w}\right]^{\eta}\left(\overline{A(t)^{1/\eta}}\right)^{\eta} = nZ(t)\frac{\overline{A(t)^{1/\eta}}}{E\left[\overline{A(t)^{1/\eta}}\right]}.$$

This expression shows that both sectoral and average idiosyncratic productivity shocks have positive impact on sectoral consumption and output, as expected. Finally, the sectoral price level is simply the ratio of the exogenously given nominal output, growing at the constant rate g, and the real output.

B Appendix: Additional Tables

Table 5: Data Summary - List of Items

Product	**CPI category**	**CPI Weight (HU 2006)**
Short loin	Unprocessed food	0.267
Spare rib	Unprocessed food	0.267
Pork leg	Unprocessed food	0.267
Flitch	Unprocessed food	0.267
Beef round	Unprocessed food	0.033
Pork liver	Unprocessed food	0.042
Chicken ready to cook	Unprocessed food	0.223
Luncheon meat	Unprocessed food	0.038
Live carp	Unprocessed food	0.029
Eggs	Unprocessed food	0.376
Cottage cheese	Processed food	0.308
Lard	Unprocessed food	0.095
Husked rice, unpolished	Processed food	0.058
White bread	Processed food	0.321
Granulated sugar	Processed food	0.169
Powdered sugar	Processed food	0.169
Red onions	Unprocessed food	0.075
Lemons	Unprocessed food	0.083
Bananas	Unprocessed food	0.083
Oranges	Unprocessed food	0.083
Dried beans	Processed food	0.016
Lentil	Processed food	0.016
Poppy seeds	Processed food	0.042
Salted hazelnut	Processed food	0.042
Pepper	Processed food	0.093
Salt	Processed food	0.093
Men's undershirt	Clothes	0.039
Cement	Non-energy industrial goods	0.031
Lime hydrate	Non-energy industrial goods	0.031
Bath-tub	Non-energy industrial goods	0.031
Bed-sheet	Non-energy industrial goods	0.055
Synthetic duvet	Non-energy industrial goods	0.055
Synthetic blanket	Non-energy industrial goods	0.055
Cotton table-cloth	Non-energy industrial goods	0.055
Terry hand towel	Non-energy industrial goods	0.055
Enameled cooking pot	Non-energy industrial goods	0.033
Toothbrush	Non-energy industrial goods	0.067
Petrol, unleaded 95 octane	Energy (oil) products	1.186
Petrol, unleaded 98 octane	Energy (oil) products	1.186
PVC ball	Non-energy industrial goods	0.034
Video tape, empty	Non-energy industrial goods	0.054
Rose	Non-energy industrial goods	0.056
Rental fee of wedding dress	Services	0.016
Men's haircut	Services	0.118
Driving lessons	Services	0.316
Photo enlargement	Services	0.099
TOTAL	–	**7.127**

Table 6: Relative Price Standard Deviations, 46 products

Product	**SK-SK**	**HU-HU**	**SK-HU**
Short loin	0.087	0.085	0.111
Spare rib	0.096	0.091	0.119
Pork leg	0.098	0.083	0.117
Flitch	0.117	0.093	0.120
Beef round	0.095	0.117	0.112
Pork liver	0.160	0.156	0.169
Chicken ready to cook	0.095	0.112	0.117
Luncheon meat	0.204	0.197	0.224
Live carp	0.139	0.087	0.143
Eggs	0.139	0.114	0.169
Cottage cheese	0.084	0.115	0.144
Lard	0.206	0.264	0.273
Husked rice, unpolished	0.159	0.174	0.218
White bread	0.117	0.130	0.151
Granulated sugar	0.082	0.067	0.136
Powdered sugar	0.088	0.092	0.120
Red onions	0.297	0.253	0.308
Lemons	0.154	0.185	0.179
Bananas	0.156	0.166	0.187
Oranges	0.219	0.272	0.277
Dried beans	0.194	0.179	0.197
Lentil	0.157	0.186	0.197
Poppy seeds	0.177	0.231	0.215
Salted hazelnut	0.187	0.197	0.208
Pepper	0.278	0.190	0.254
Salt	0.127	0.174	0.157
Men's undershirt	0.164	0.194	0.187
Cement	0.063	0.074	0.092
Lime hydrate	0.093	0.325	0.314
Bath tub	0.087	0.140	0.138
Bed sheet	0.107	0.119	0.125
Synthetic duvet	0.128	0.206	0.180
Synthetic blanket	0.117	0.176	0.156
Cotton table-cloth	0.203	0.222	0.227
Terry hand towel	0.144	0.194	0.174
Enameled cooking pot	0.186	0.194	0.198
Toothbrush	0.195	0.185	0.224
Petrol, unleaded 95	0.022	0.018	0.110
Petrol, unleaded 98	0.009	0.018	0.154
PVC ball	0.201	0.174	0.194
Video tape, empty	0.157	0.146	0.156
Rose	0.135	0.284	0.253
Rental fee of wedding dress	0.096	0.135	0.125
Men's haircut	0.127	0.109	0.121
Driving lessons	0.095	0.095	0.105
Photo enlargement	0.120	0.104	0.119
Median	**0.131**	**0.161**	**0.163**
1st quartile	**0.096**	**0.105**	**0.122**
3rd quartile	**0.173**	**0.194**	**0.206**

Table 7: Data Moments, 46 products

Product	$frequency$	$size$	$\beta_D * 10^4$	$\beta_B * 10^3$	$e^{\beta_B/\beta_D} - 1$
Short loin	0.521	0.074	18.55	62.89	$5 * 10^{14}$
Spare rib	0.525	0.083	19.05	58.25	$2 * 10^{13}$
Pork leg	0.485	0.076	11.18	62.54	$2 * 10^{24}$
Flitch	0.482	0.094	19.97	38.46	$2 * 10^{8}$
Beef round	0.258	0.070	19.35	20.45	38,964
Pork liver	0.211	0.116	15.24	4.95	25
Chicken ready to cook	0.434	0.075	8.04	32.85	$6 * 10^{17}$
Luncheon meat	0.231	0.118	23.41	8.37	35
Live carp	0.165	0.087	29.16	0.69	0.27
Eggs	0.500	0.109	22.54	44.54	$4 * 10^{8}$
Cottage cheese	0.323	0.074	11.27	9.53	4,708
Lard	0.277	0.144	33.47	29.03	5,852
Husked rice, unpolished	0.340	0.090	16.88	13.12	2,380
White bread	0.179	0.088	14.07	2.24	3.91
Granulated sugar	0.321	0.066	8.76	25.83	$6 * 10^{12}$
Powdered sugar	0.269	0.079	3.81	12.20	$8 * 10^{13}$
Red onions	0.572	0.241	49.05	45.33	10,313
Lemons	0.566	0.136	19.40	20.83	46,046
Bananas	0.723	0.144	18.20	14.49	2,875
Oranges	0.660	0.186	27.05	33.42	$2 * 10^{5}$
Dried beans	0.255	0.112	22.00	-0.72	-0.28
Lentil	0.272	0.107	15.86	0.59	0.45
Poppy seeds	0.298	0.128	21.00	3.26	3.73
Salted hazelnut	0.264	0.113	16.63	-0.92	-0.42
Pepper	0.257	0.169	32.12	3.23	1.74
Salt	0.190	0.116	10.92	12.16	68,526
Men's undershirt	0.187	0.092	13.80	3.97	17
Cement	0.167	0.054	16.79	16.70	20,908
Lime hydrate	0.134	0.110	20.11	75.28	$2 * 10^{16}$
Bath tub	0.109	0.062	1.83	2.28	$3 * 10^{5}$
Bed sheet	0.132	0.077	14.77	3.94	13
Synthetic duvet	0.141	0.096	13.83	5.35	47
Synthetic blanket	0.165	0.076	19.89	6.33	23
Cotton table-cloth	0.194	0.111	26.27	-1.18	-0.36
Terry hand towel	0.167	0.094	11.85	7.91	792
Enameled cooking pot	0.185	0.101	34.17	27.25	2,909
Toothbrush	0.198	0.108	51.47	1.76	0.41
Petrol, unleaded 95	0.914	0.028	11.20	28.41	10^{11}
Petrol, unleaded 98	0.896	0.028	5.60	65.24	$4 * 10^{50}$
PVC ball	0.156	0.124	34.62	29.17	4,572
Video tape, empty	0.144	0.087	77.80	8.40	1.94
Rose	0.499	0.172	53.16	44.70	4,490
Rental fee of wedding dress	0.090	0.086	33.24	27.55	3,981
Men's haircut	0.071	0.129	33.77	20.19	394
Driving lessons	0.130	0.068	66.10	7.32	2.03
Photo enlargement	0.050	0.121	12.90	16.86	$5 * 10^{5}$
Median	**0.256**	**0.095**	**19.20**	**13.81**	**4,236**
1st quartile	**0.166**	**0.077**	**13.81**	**4.22**	**14**
3rd quartile	**0.470**	**0.117**	**28.63**	**29.14**	$4 * 10^{5}$

Table 8: Structural Parameters, 46 products

Product	ψ	σ_A	d	b	$e^{b/d}-1$	60^{-d}
Short loin	0.0032	0.053	0.155	1.12	1386	0.53
Spare rib	0.0040	0.060	0.150	1.07	1190	0.54
Pork leg	0.0038	0.053	0.135	1.19	7098	0.58
Flitch	0.0057	0.065	0.152	0.92	426	0.54
Beef round	0.0068	0.041	0.189	0.84	85	0.46
Pork liver	0.0218	0.067	0.162	0.51	23	0.52
Chicken ready to cook	0.0044	0.050	0.127	1.03	3334	0.59
Luncheon meat	0.0206	0.068	0.178	0.55	22	0.48
Live carp	0.0154	0.049	0.221	0.24	1.96	0.40
Eggs	0.0071	0.076	0.149	0.95	558	0.54
Cottage cheese	0.0061	0.046	0.154	0.69	89	0.53
Lard	0.0259	0.087	0.177	0.78	80	0.48
Husked rice, unpolished	0.0084	0.056	0.162	0.68	67	0.52
White bread	0.0147	0.050	0.180	0.40	8.31	0.48
Granulated sugar	0.0049	0.041	0.145	1.03	1215	0.55
Powdered sugar	0.0082	0.047	0.111	0.93	4707	0.64
Red onions	0.0202	0.182	0.142	0.78	247	0.56
Lemons	0.0085	0.101	0.129	0.72	263	0.59
Bananas	0.0043	0.121	0.115	0.54	103	0.62
Oranges	0.0091	0.149	0.122	0.78	592	0.61
Dried beans	0.0172	0.066	0.208	-0.07	-0.29	0.43
Lentil	0.0149	0.064	0.175	0.14	1.17	0.49
Poppy seeds	0.0191	0.078	0.168	0.31	5.22	0.50
Salted hazelnut	0.0168	0.067	0.206	-0.20	-0.62	0.43
Pepper	0.0375	0.100	0.181	0.25	2.98	0.48
Salt	0.0238	0.066	0.146	0.81	253	0.55
Men's undershirt	0.0155	0.053	0.174	0.47	14	0.49
Cement	0.0063	0.030	0.208	1.10	202	0.43
Lime hydrate	0.0284	0.062	0.185	1.85	22911	0.47
Bath tub	0.0123	0.035	0.114	0.68	402	0.63
Bed sheet	0.0148	0.043	0.195	0.52	13	0.45
Synthetic duvet	0.0211	0.054	0.177	0.57	23	0.48
Synthetic blanket	0.0120	0.043	0.202	0.63	22	0.44
Cotton table-cloth	0.0215	0.064	0.233	-0.14	-0.45	0.39
Terry hand towel	0.0178	0.053	0.165	0.70	68	0.51
Enameled cooking pot	0.0187	0.058	0.207	0.93	88	0.43
Toothbrush	0.0201	0.062	0.238	0.30	2.53	0.38
Petrol, unleaded 95	0.0000	0.028	0.137	0.64	107	0.57
Petrol, unleaded 98	0.0001	0.028	0.096	0.79	3663	0.67
PVC ball	0.0316	0.070	0.201	0.90	87	0.44
Video tape, empty	0.0173	0.049	0.276	0.55	6.48	0.32
Rose	0.0165	0.121	0.170	0.80	106	0.50
Rental fee of wedding dress	0.0258	0.048	0.239	1.80	1865	0.38
Men's haircut	0.0659	0.073	0.227	1.06	105	0.39
Driving lessons	0.0122	0.038	0.289	0.55	5.71	0.31
Photo enlargement	0.0912	0.072	0.190	1.13	377	0.46
Median	**0.0152**	**0.059**	**0.174**	**0.71**	**89**	**0.49**
1st quartile	**0.0069**	**0.049**	**0.146**	**0.52**	**14**	**0.44**
3rd quartile	**0.0205**	**0.069**	**0.202**	**0.93**	**420**	**0.55**