The Geography of Consumer Prices*

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July 19, 2011

Abstract

We argue that the underlying width of the border in international price determination is a trivial fraction of the corresponding Engel and Rogers (1996) reduced form estimate. We develop a two-country, multi-region, dynamic, stochastic equilibrium model of monopolistic competition with costly price adjustment and cross-location shopping. The optimal price is proportional to a weighted average of market prices, with weights negatively related to shopping costs. We calibrate structural distance and border parameters to a unique panel of store-level prices, and conclude that price adjustment costs directly account for about a quarter of the reduced form border width.

Keywords: international relative prices, border effect, gravity, menu costs, structural calibration

*For financial support, we thank the CEU Research Support Scheme and GDN RRC-10 grants.

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1 Introduction

How does geography, particularly, distance and the national border 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]

Since Engel and Rogers (1996), the common wisdom in international macroeconomics is that distance adjusted relative prices are much more volatile across than within countries, indicating a giant *border effect* in international price determination. We argue that the underlying width of the border is a trivial fraction of the reduced form one measured in Engel and Rogers and subsequent analyses. In doing so, 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. Second, we apply the quantitative model to store-level price data to pin down the underlying structural distance and border parameters governing relative price dynamics via a moment matching procedure.

In the model, a finite 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.

A standard result in models of monopolistic competition is that stores care about the average of other stores' price as they optimally set their own one. 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 prevailing at more remote locations. To stress the basic mechanism at work, a stylized example with 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

[1] See Obstfeld and Rogoff (2001).

change in relative prices in this region, adjusting more their relative demand, as they are located closer thus need to travel less 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 price adjustment when they reset their nominal price in response to stochastic shocks. Both of these modeling assumptions are firmly rooted in microeconomic evidence. First, basic descriptive patterns in international pricing for particular individual products 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 to the distance and the border between locations.[3] Furthermore, misalignments in cross-location price differentials are relatively slow to fade away, especially at higher 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 can influence pricing behavior. Finally, in a distinct strand of literature, empirical studies drawing on highly disaggregated store-level data collected in several different countries 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]

The point of departure for the empirical analysis 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

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

[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).

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 slightly different data and empirical specifications.[7] Gorodnichenko and Tesar (2009), however, 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 ultimate challenge we take up in this paper is to directly confront 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 of retail-level price quotations recorded in two small, neighboring economies, Hungary and Slovakia. The 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. These data compare most closely to the ones used in Broda and Weinstein (2008). While individual items in it are less finely defined, our sample exhibits a wider range of product categories including durable goods and services as well. In addition, distances in our sample are relatively small providing ample opportunity for consumers to arbitrage price differentials away.

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 estimated *à la* Engel and Rogers (1996). The results, first, confirm that in reduced form regressions both geographical distance and the border are highly significant, and the implied width of the border is truly giant. At the same time, the structurally calibrated width of the border is a tiny fraction of its reduced form counterpart. We show that the structural model maps distance- and border-related shopping costs to relative price differentials in a highly non-linear way, so that it amplifies the structural width of the border. Quantitatively, we find that fixed costs to price adjustment directly account for 22 percent of the deviation between structural and reduced form estimates of the width of the

[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.

border. Overall, we argue that our structural approach explicitly conditions on frictions both in the commuting and the price setting process, allowing one to assess their direct contribution to reduced form border width.

The rest of the paper is organized as follows. In Section 2 we describe our model of international pricing, highlighting the role geographical frictions play in the propagation mechanism. 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 finite number of single-product stores, n_r. The total number of stores is $\sum_{r=1}^{R} n_r = n$. 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 $n_1 + ... + n_{R-1} < i \leq n$ 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 aggregate real output, α_r is assumed to be equal to the proportion of stores in that region, n_r/n.

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 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 $r(i)$. The shopping cost creates a wedge between the price the consumer actually pays and the shopping-cost augmented price, in short, the "perceived price", that is relevant in determining her demand. That is, the price $P(i)$ 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 $\log\left(1 + \tau^j_{r(i)}\right) = d \cdot \log D\left(r(i), j\right) + b \cdot B\left(r(i), j\right)$, where $D\left(r(i), j\right)$ is a continuous variable representing distance between store $r(i)$ and consumer j, and $B\left(r(i), j\right)$ is a binary variable taking on a value of one if 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 $D\left(r(i), j\right)$ 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 switch sign 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, $C^j_t = \left[\sum_{i=1}^n C^j_t(i)^{\frac{\theta-1}{\theta}}\right]^{\frac{\theta}{\theta-1}}$. L^j_t is the amount of labor supplied by consumer j at time t. 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. As in Golosov and Lucas (2007) and Midrigan (2011), we assume perfectly elastic labor supply.

The budget constraint of consumer j is

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

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 related to growing money supply.

The solution to this optimization problem gives rise to demand by consumer

j in store i as

$$C_t^j(i) = C_t^j \left[\frac{(1+\tau_{r(i)}^j) P_t(i)}{P_t^j} \right]^{-\theta},$$

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

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

That is, demand of consumer j at store i relative to her total demand depends on relative perceived prices, i.e. the prices she perceives at the particular store 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 generate its output, $Y_t(i)$. $A_t(i)$ is a stochastic idiosyncratic productivity shock specific to store i, while Z_t is a deterministic trend in aggregate productivity common to all stores. The production function of store i is thus

$$Y_t(i) = Z_t A_t(i) L_t(i),$$

where we assume constant returns-to-scale technology. Sectoral productivity is growing at a constant rate $g_Z = \log Z_{t+1} - \log Z_t$. Idiosyncratic productivity follows an AR(1) process, with 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 labor input as

$$L_t(i) = \frac{Y_t(i)}{Z_t A_t(i)}.$$

Labor demand is met by the representative agents' perfectly elastic labor supply.

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

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

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

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

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 rate g_Z, inflation is $g_{PY} - g_Z$. We write the stationary profit function for store i by normalizing nominal profit by per-store nominal output, $\overline{P}_t(i)C_t$, as

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

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" $w_t \left[\frac{C_t}{Z_t} \right]$ by ζ_t, the stationary profit function of store i simplifies to

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

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

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

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 program is

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

In sum, the equilibrium conditions in the model are as follows. Consumers maximize their expected lifetime utility under the budget constraint, taking prices and wages as given, stores solve their dynamic decision 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 aggregate productivity grows by a constant rate g_Z, which, together with the constant nominal growth assumption, implies no aggregate uncertainty, hence aggregate state variables are equal to their equilibrium values. In particular, $g_{Z,t} = g_Z$ and $\pi_t = g_{PY} - g_Z$ for all t. In the absence of a closed-form solution, we calculate numerically the equilibrium values of the other two aggregate state variables, ζ_t and Ω_t.

In particular, 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 equilibrium inflation rate, $\pi = g_{PY} - g_Z$, we find the value function and the corresponding policy function by value-function iteration, using a fine grid over the individual relative price and idiosyncratic productivity. 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. 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. 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 iterate in ζ until the average relative price in the resulting steady-state distribution is exactly zero.

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 near to them. Formally, geographical location is part of the state determining the choice of nominal price at a particular 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 store i, $\overline{P}_t(i)$.

The more detailed argument on how geography matters in microeconomic pricing decision proceeds in two steps. 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, this store 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, $P_t(k)$,

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

The positive sign of this derivative implies that the representative consumer in region j faces a higher perceived price. In addition, the derivative is decreasing in $\tau_{r(k)}^j$, so 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.

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

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

That is, the average price rises in response to the shock. This result also shows that the price 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 of price setting 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.[8]

The items we consider are extracted from the universe of several hundred

[8] Table 8 in Appendix B lists all 46 items in the sample.

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. In terms of coverage, this set of products contains about 7.1% of the entire Hungarian CPI basket in 2006.

Table 1: Items by CPI Categories

CPI Category	**Number of Products**	**CPI Weight (HU 2006)**
Unprocessed food	15	2.23
Processed food	11	1.33
Clothes	1	0.04
Durable goods	13	0.61
Energy products	2	2.37
Services	4	0.55
TOTAL	**46**	**7.13**

As they are likely to have negligible impact on patterns in cross-border shopping, as highlighted in the map in Figure 1, we also drop prices observed in regions further away from the border. The resulting final sample consists of prices recorded 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.[9] Finally, we note that these locations serve as an attractive environment to analyze the border effect. In particular, as nationalities live mixed together in the area we zoom on, 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 unlikely to be a major source of border frictions.

For the average product in our sample, prices are observed in about a total of 90 distinct retail stores per month,[10] and over a 60 month time-span between

[9]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

[10]There are about 170 stores on average in the full sample, when we include all counties in the two countries. The retail stores are mostly independent ones in the sense that they do not belong to a hypermarket chain.

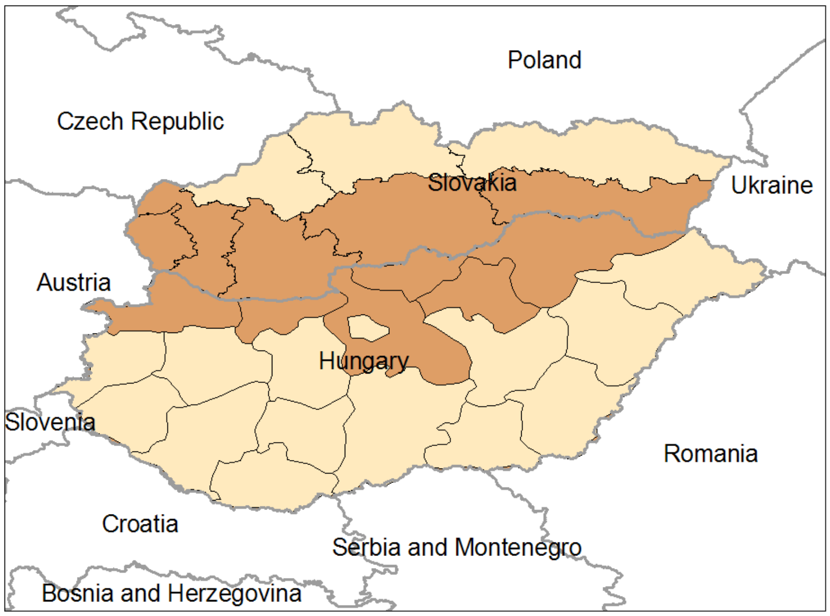

Figure 1: Regions in Hungary and Slovakia

January 2002 through December 2006. The final sample comprises of a total of about 260,000 individual price observations. We perform two standard data corrections in this sample. First, when the price is not observed for some reason and a statistical procedure is used to generate an "artificial"price quote, we replace these imputed prices with the last normal price observation. Second, we filter out all sales-related price changes.[11]

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

[11]The number of imputed observations is 402 or about 0.15% of observations in the whole sample, while sales filtering reduces the median frequency of price changes from 0.274 to 0.256 (for the mean frequency, the reduction is from 0.328 to 0.311).

in product-level relative prices. The figures we report in Table 2 and Table 9 in Appendix B are simple unweighted averages of relative price standard deviations calculated between all possible pairs of stores within and across countries.[12] 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 Price			Changes in Relative Price		
	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 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 employ 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

[12]Throughout the paper, we present only the cross-product quartile figures, leaving the detailed product-level results reported in the Appendix.

variation is still larger than variation in any of the two countries for 28 products. 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 regression 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

$$V(P_{j,k}) = dummies + \beta_D log(D_{j,k}) + \beta_B B_{j,k} + u_{j,k}, \tag{1}$$

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. As in 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 10 in Appendix B 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.[13]

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 need to travel within a country to have the same relative price variation as the one implied by crossing the border while traveling the same baseline distance. Formally, the border width is the solution to the equation, $\beta_D \ln(D + W) = \beta_D \ln D + \beta_B$, so

[13] 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.

that $W = D(e^{\beta_B/\beta_D} - 1)$, i.e. border increases the distance between locations by a factor of $e^{\beta_B/\beta_D} - 1$. The last column in Table 3 reports the median reduced form border width estimates (for the product-level estimates, see Table 10 in the Appendix). Defined as the factor above, or the distance equivalent of the border evaluated at the distance of 1 minute, the median width of the border is 4,236. This factor of proportionality is somewhat smaller than the one of 75,000 estimated in Engel and Rogers (1996), and much 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. Indeed, our estimates exceed those of 720, or 328, depending on the specification, Broda and Weinstein (2008) reports in a sample of bar-code level disaggregated, extremely homogenous products. Taken together, our data indicate sizeable borders effects, comparable to ones established in related studies of international relative prices.

4.2 Model Calibration

The huge width of the reduced form border estimates may reflect the impact of omitted variables. Since Engel and Rogers (1996), some of these elements are associated with the amplifying effect of 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 specify the model at the monthly frequency, separately for each individual product. In 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 to $\beta = 0.96^{1/12} = 0.9966$. We fix the elasticity of substitution parameter at $\theta = 5$, implying a 25% markup for monopolistically competitive stores. This value is a compromise between the elasticities of 7 and 3 set in Golosov and Lucas (2007) and Midrigan (2011), respectively. Approximating well the actual figure both in Hungary and Slovakia during the 2002-2006 period, the growth rate of nominal output is set to $g_{PY} = 0.0075$. We also fix the monthly productivity growth rate at $g_Z = 0.0025$, implying an annual inflation rate of 6%, with these figures matching the average inflation and real growth rates in Hungary and Slovakia in the sample period. We also assume that the persistence in the idiosyncratic technology shock process is $\rho_A = 0.5$, a figure in the vicinity of 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).

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 summary statistics for all of these data moments are reported in Table 3, while product-level estimates are listed in Table 10 of the Appendix. As we demonstrate it in the next subsection, the menu cost and the shock volatility parameters primarily determine the frequency and absolute size of price changes,[14] 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 quartiles of the calibrated structural parameters are reported in Table 4 (the parameters for the 46 products are in Table 11 of the Appendix). The median menu cost parameter, calculated as the median value for the menu cost multiplied by the median frequency of price adjustment, is 0.0152. This implies that firms spend about 0.39% of their revenue 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, however small actual distance are. The results are quite homogenous 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}.[15] This calculation implies that, for the median product, due to distance-related shopping costs, the average consumer needs a 51% discount to travel to a loca-

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

[15] 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. $\frac{P_1}{P_2} < 60^{-d}$.

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

tion 60 minutes away. The interquartile range of the estimated discount is again relatively tight, [0.45; 0.56]. For a 10 minute shopping trip, the corresponding discount is 33 percent. Finally, we note that these figures provide an upper bound on the distance and the corresponding required discount parameters as they are calculated for single-product purchases.

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, $(e^{b/d}-1)$, 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 sizeable,[16] it is only about 2.1 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 width, especially for products with a relatively wide underlying border.

4.3 Reduced Form *vs.* Structural Width

Why are reduced form estimates of the border width so much larger than structural ones? To answer this question, first, we investigate whether there is anything intrinsic in our model artificially generating a reduced form border effect, independently of the structural border and distance parameters. We carry out two experiments at the product level. In the first one, we set the structural border parameter, b, to zero, leaving the rest of the calibrated parametrization unchanged, and calculate the resulting reduced form border and distance parameters, β_B and β_D. In the second experiment, we shut down the structural distance parameter, d, without modifying anything else.

The results of these model simulations are displayed in the second and third

[16] In our data, the unweighted 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.

rows of Table 5. While the median frequency and size of price changes are mostly unaffected, when the structural border coefficient is set to zero, as the median β_B shrinks zero and the median β_D remains positive though smaller than in the baseline case, the reduced form border width falls to zero. In the second experiment, when the structural distance parameter is shut down to zero, the reduced form distance becomes zero, with the median border decreasing but staying positive, hence the reduced form border width converging to infinity. These findings suggest that both geographic model parameters are instrumental in identifying the reduced form border effect.

Table 5: Data Moments in Model Versions

	frequency	*size*	$\beta_D * 10^4$	$\beta_B * 10^3$	$e^{\beta_B/\beta_D} - 1$
Calibrated model (data)	0.256	0.095	19.20	13.81	4,236
model with $b = 0$	0.272	0.094	9.19	-0.12	0
model with $d = 0$	0.271	0.092	0.07	3.26	∞
model with $\phi = 0.001$	0.759	0.074	35.26	26.00	1,521
model with $\sigma_A = 0.018$	0.077	0.062	3.65	3.37	4,971

A related question is how precisely the reduced from distance and border coefficients identify the structural distance and border parameters. To address this issue, we simulate the model for a range of structural distance and border parameters for a randomly selected product.[17] Table 6 displays the results. First, the reduced form border and distance coefficients shown in panel 1 and 2, respectively, are quite sensitive to changes in the corresponding structural parameters. In this sense, these conditional moments clearly identify the underlying structural parameters. Second, again, we see that whenever one of the structural parameters is zero, the corresponding reduced form coefficient is also close to zero. Third, regarding cross-effects, while the structural border parameter has only a minor influence on the reduced form distance coefficient, the structural distance parameter has a relatively large impact on the reduced form border coefficient.

Given the simulated reduced form parameters shown in Table 6, next, we calculate the relationship between structural and reduced form border width, $e^{b/d} - 1$ and $e^{\beta_B/\beta_D} - 1$, for this particular product. The results reported in Table 7 indicate that for moderate structural border width, for values below about 10, the reduced form width is similar to the structural one; but for larger structural width, the reduced form width explodes. To conclude, while the

[17]The simulation results are robust to the choice of the product.

structural model does not produce an artificial border effect in the absence of a genuine one, it does inflate the existing border width to a large extent.

Table 6: Effect of Structural (b, d) on Reduced Form (β_B, β_D) Parameters

PANEL 1: SIMULATED β_B					
	Structural distance parameter (d)				
Structural border (b)	0	0.05	0.1	0.15	0.2
0	-0.05	-0.06	-0.04	-0.15	-0.18
0.2	0.15	0.43	0.88	1.97	3.39
0.4	0.94	1.77	3.79	7.02	10.10
0.6	2.90	5.26	9.78	16.51	24.26
0.8	7.54	12.14	21.94	35.24	47.30
1	16.54	24.72	36.54	60.57	97.89
PANEL 2: SIMULATED β_D					
	Structural distance parameter (d)				
Structural border (b)	0	0.05	0.1	0.15	0.2
0	0.19	0.62	2.88	10.28	28.81
0.2	0.14	0.80	4.22	14.14	36.60
0.4	0.16	1.06	5.22	16.90	42.22
0.6	0.11	1.18	5.86	18.32	45.45
0.8	0.24	1.26	6.23	19.06	46.49
1	0.18	1.30	6.37	19.48	47.17

We now turn to the question of whether costly price adjustment and idiosyncratic shocks can explain, at least partially, the difference between structural and reduced form estimates of border width. We start out with performing model simulations using the calibrated and preset structural parameters, while varying the parameter values for menu cost, ϕ, and idiosyncratic shock standard deviation, σ_A, over the relevant range.

Rows 4 and 5 in Table 5 display the results. If menu costs are small, $\phi = 0.001$, the median frequency of price changes increases to 75.9%, and the median average absolute size of price changes falls to 0.074, as expected. The estimated reduced form coefficients both jump up, so the effect of eliminating price stickiness on the estimated reduced form border is ambiguous; for the majority of products it decreases, and the median border width also shrinks from 4,236 to 1,521.[18] As the idiosyncratic shock is reduced to σ_A=0.018, the median frequency, size, and reduced form distance and border coefficients all shrink but the estimated border width changes only slightly.[19]

[18]The relative ranking of products varies little, so this median is sensitive to a few products in the middle of the original ranking. As the width is an exponential function, the seemingly large decline in the median width is actually not particularly giant if we consider the median estimated ratio of β_B/β_D.

[19]As σ_A goes to zero, both reduced form coefficients converge towards zero, so the border width, which is a function of their ratio, becomes undefined.

Table 7: Structural and Reduced Form Border Widths

PANEL 1: Structural widths ($e^{b/d}-1$)					
	Structural distance parameter (d)				
Structural border (b)	0	0.05	0.1	0.15	0.2
0	–	0	0	0	0
0.2	∞	54	6	3	2
0.4	∞	2,980	54	13	6
0.6	∞	162,754	402	54	19
0.8	∞	$9*10^6$	2,980	206	54
1	∞	$5*10^8$	22,025	785	147

PANEL 2: Reduced form widths $e^{\beta_B/\beta_D}-1$					
	Structural distance parameter (d)				
Structural border (b)	0	0.05	0.1	0.15	0.2
0	–	0	0	0	0
0.2	44,993	215	7	3	2
0.4	$3*10^{25}$	$2*10^7$	1,422	63	10
0.6	$3*10^{114}$	$2*10^{19}$	$2*10^7$	8,200	207
0.8	$3*10^{136}$	$7*10^{41}$	$2*10^{15}$	10^8	26,219
1	∞	$4*10^{82}$	$8*10^{24}$	$3*10^{13}$	10^9

To study the effect of price stickiness and idiosyncratic shocks on border width more systematically, separately for each product, we simulate the calibrated model at counterfactual values of the menu cost and idiosyncratic shock standard deviation parameters. For the menu cost, we choose 10, 20 ... and 150 percent, for the shock standard deviation 50, 75, 100 and 125 percent of the baseline calibration as counterfactuals. Based on data from these simulations performed 60 times per product, we then estimate the regression equation

$$R_i = \alpha_0 + \alpha_1\phi_i + \alpha_2\sigma_i + \varepsilon_i,$$

where the index for model simulation is $i = 1, \ldots, 2,760$, the relative border width in simulation i is $R_i = \left(\frac{\beta_{B,i}}{\beta_{D,i}} - \overline{\left(\frac{\beta_{B,i}}{\beta_{D,i}}\right)}\right) / \overline{\left(\frac{\beta_{B,i}}{\beta_{D,i}}\right)}$, and ϕ_i and σ_i are the corresponding menu cost and idiosyncratic shock parameters.[20] The estimation results show that α_1 is significantly positive, $\widehat{\alpha}_1 = 1.94$, implying that higher menu costs through more price stickiness lead to higher reduced form border width. In particular, at the median menu cost of $\phi = 0.0152$, relative border width is larger by 0.0296 than it would be under flexible prices, $\phi = 0$. To express this figure in terms of absolute border width, we multiply it by the average of β_B/β_D for the median product, 8.3497. This implies that, relative to the flexible

[20] To account for the different size of the border for the different products, we calculate width relative to the item-specific average width of the border.

price case, the absolute border width is larger by 0.0296*8.3497=0.2468, or its exponential by a factor of $e^{0.2468} = 1.28$. That is, while we cannot give an exact decomposition of how shopping and pricing frictions give rise to the enormous reduced form border width, we show that the menu cost directly amplify the estimated reduced form border width by 28 percent relative to the flexible price model. In this sense, as the structural width is 2.1 percent of the actual reduced form one, menu costs can explain about a quarter of the difference between the reduced form and structural width.

Finally, we perform the regression analysis above with a cross-product term for menu cost and shock volatility added to the specification. The estimation results show that the cross-product term is significantly negative, while shock volatility in itself is insignificant, implying that price stickiness has larger impact on the estimated reduced form border width when idiosyncratic shocks are smaller. In other words, idiosyncratic shocks seem to have only an indirect effect on the estimated border width, through price stickiness. Quantitatively, median price stickiness increases the estimated reduced form border width by a factor of about 1.28, as in the benchmark specification.

5 Conclusions

The challenge we take up in this paper is spelled out in the concluding section of Engel and Rogers (1996): "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. "

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 the implied width of the border is a trivial fraction of the corresponding reduced form estimate. In addition, we show that menu costs account for about a quarter of this discrepancy. 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, it 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, we assume that the persistence of the productivity process is constant and preset. One could think of bringing in further information from other moments and have this model parameter calibrated to the data as well. Finally, it would clearly be desirable to expand the geographical and product coverage of our sample of prices. 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. Then the optimal relative price in store i is

$$p_t^*(i) = \left[\frac{\theta\zeta_t}{\theta-1}\right] A_t(i)^{-1},$$

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

$$\frac{C_t^*(i)}{C_t/n} = \left[\frac{\theta\zeta_t}{\theta-1}\right]^{-\theta} A_t(i)^{\theta},$$

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, $C_t^*(i)$ gives $\frac{C_t^*}{n} = \left[\frac{\sum_{i=1}^n C_t^*(i)^{\frac{\theta-1}{\theta}}}{n}\right]^{\frac{\theta}{\theta-1}}$, which can be rearranged as

$$\frac{\theta\zeta_t}{\theta-1} = \left[\frac{\sum_{i=1}^n A_t(i)^{\theta-1}}{n}\right]^{\frac{1}{\theta-1}},$$

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

$$p_t^*(i) = \left[\frac{A_t(i)}{\overline{A_t}}\right]^{-1}.$$

Also, relative output is obtained as

$$\frac{C_t^*(i)}{C_t/n} = \left[\frac{A_t(i)}{\overline{A_t}}\right]^{\theta}.$$

These results show that optimal relative prices and consumptions depend on relative productivities.

Returning to the aggregation equation, $\frac{\theta\zeta_t}{\theta-1} = \overline{A_t}$, $\zeta_t = w_t \frac{C_t}{nZ_t}$ can be writen as $\frac{\theta-1}{\theta}\overline{A_t}$. We then normalize the model so that the constant normalized wage w is equal to the expected value of $\frac{\theta-1}{\theta}\overline{A_t}$, and hence the term $\left[\frac{C_t}{nZ_t}\right]$ fluctuates around unity, with the exact value depending on $\overline{A_t}$ relative to its expected value.

Next, from $\frac{\theta\zeta_t}{\theta-1} = \overline{A_t}$, we express $\zeta_t = w_t \frac{C_t}{nZ_t}$ as

$$w_t \frac{C_t}{nZ_t} = \frac{\theta - 1}{\theta} \overline{A_t},$$

and hence the total real consumption is

$$C_t = nZ_t \frac{\theta - 1}{\theta w} \overline{A_t} = nZ_t \frac{\overline{A_t}}{E\left[\overline{A_t}\right]}.$$

This expression shows that both sectoral and average idiosyncratic productivity 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 real output.

B Appendix: Additional Tables

Table 8: 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	Durable goods	0.031
Lime hydrate	Durable goods	0.031
Bath-tub	Durable goods	0.031
Bed-sheet	Durable goods	0.055
Synthetic duvet	Durable goods	0.055
Synthetic blanket	Durable goods	0.055
Cotton table-cloth	Durable goods	0.055
Terry hand towel	Durable goods	0.055
Enameled cooking pot	Durable goods	0.033
Toothbrush	Durable goods	0.067
Petrol, unleaded 95 octane	Energy products	1.186
Petrol, unleaded 98 octane	Energy products	1.186
PVC ball	Durable goods	0.034
Video tape, empty	Durable goods	0.054
Rose	Durable 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 9: 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 10: 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 11: 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**