The law of one price without the border: the role of distance versus sticky prices*

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Abstract

We examine the role of nominal price rigidities in explaining the deviations from the Law of One Price (LOP) across cities in Japan. Focusing on intra-national relative prices isolates the border effect and thus enables us to extract the pure effect of sticky prices. A two-city model with nominal rigidities and transportation costs predicts that the variation of LOP deviations is lower for goods with less frequent price adjustment after controlling for the distance separating the cities. Using retail price data for individual goods and services collected in Japanese cities, we find strong evidence supporting this prediction. Adapting the Engel and Rogers (1996) regression framework to our theoretical setting, we quantify the separate roles of nominal rigidities and trade costs (proxied by distance) in generating LOP variability. Our estimates suggest that the distance equivalent of nominal rigidities can be as large as the 'width' of the border typically found in the literature on international LOP deviations. The findings point to both the utility of the regression framework in identifying qualitative effects (i.e., sign of a coefficient) and the challenges interpreting their quantitative implications.

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Keywords: Border effect, Good-level real exchange rate, Nominal price rigidity, Relative price variability

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1 Introduction

The failure of the strict version of the Law of One Price (LOP) between cities is often attributed to the spatial segmentation of commodity markets. As in the gravity models of trade, distance is typically used as a proxy for trade costs that handicap arbitrage across locations. In an influential paper, Engel and Rogers (1996, hereafter ER) confirmed the importance of distance in explaining the variation of the prices of similar goods in different cities. However, holding distance constant, they found that volatility was much higher for city pairs separated by a national border. They tentatively concluded that nominal price stickiness accounted for a significant portion of the magnitude of the border effect, and suggested a marriage of the new-Keynesian literature on menu costs and the new trade literature emphasizing the role of geography as a promising direction for future research.

This paper uses highly disaggregated Japanese retail price data and directly examines the role of nominal price stickiness in the variation of LOP deviations, after controlling for distance. Since we are interested in isolating the effect of nominal rigidities and transportation costs from international trade barriers and nominal exchange rate volatility, we focus on price differences across city-pairs within Japan.[1] We adapt the ER borders regression of price volatility on distance and a border dummy, dropping the border dummy and adding a good-specific proxy for price stickiness. Within this regression framework, we also quantify the importance of price stickiness in terms of physical distance, analogous to measuring the 'width' of the border in ER.

To motivate our regression model, we construct a dynamic general equilibrium model which incorporates: (i) pricing to market behavior of monopolistically competitive firms; (ii) transportation costs; and (iii) nominal price rigidities generated by Calvo pricing. These three features are common ingredients of the *New Open Economy Macroeconomics* recipe. For example, Bergin and Feenstra (2001) and Chari, Kehoe, and McGrattan (2002) employ a two-country model with these features in their attempt to explain aggregate real exchange rate fluctuations. Here the focus is on cross-sectional implications: How does the model perform in terms of explaining differences in the nature of fluctuations in LOP deviations across goods and across city-pairs?

The empirical part of our analysis employs data on the retail prices of individual goods and services and is closely related to the recent macroeconomics literature on nominal rigidities. Using US CPI micro data, Bils and Klenow (2004) find the median duration between posted price changes

[1] A similar strategy was adopted by Parsley and Wei (1996) for the US.

of 4.3 months, considerably shorter than the earlier consensus level of about a year. Using more detailed data, Nakamura and Steinsson (2008) and Klenow and Kryvtsov (2008) estimate the median duration between regular price changes to be 8-11 months and 7 months, respectively. These studies have documented both fast adjustment of retail prices over time and substantial heterogeneity in the speed of adjustment across goods.

In the context of international price convergence, Kehoe and Midrigan (2007) examine the relationship between the good-specific frequency of price changes and the persistence of good-level real exchange rates using a two-country monetary model with Calvo-type price stickiness. Crucini, Shintani, and Tsuruga (2008) extend their analysis by introducing sticky information to the model. However, none of these studies attempt to assess the separate roles of distance and empirical frequency of price changes in accounting for the variance of LOP deviations.

One stylized fact about absolute LOP deviations is the clear rejection of their long-run convergence to zero. This observation has been documented using a wide array of data sources by Goldberg and Verboven (2004), Crucini, Telmer, and Zachariadis (2005), Broda and Weinstein (2008) and Crucini and Shintani (2008). Based on these findings, we allow pricing to market with good-specific markups as well as transportation costs. In our two-city equilibrium model, deviations from the common stochastic trend in productivity is allowed to occur at the level of individual goods and cities. These productivity differences are permitted to be zero also in the long-run, nesting both the absolute and relative version of LOP in our framework.

Our main theoretical proposition is that LOP variability (around their long-run level) in the intra-national context can indeed be smaller for a sticky price economy than a flexible price economy. This contrasts to models focusing on cross-border LOP deviations where the deviations are rising in the level of price stickiness, due to the dominant role of nominal exchange rate fluctuations among cross-border pairs.

Our hypothesis is that the volatility of the relative price of a good across two Japanese cities should be positively related to the distance separating those cities and negatively related to the degree of price stickiness of the good in question. We examine these predictions pooling all available goods in an ER-like regression, an approach similar to the pooling regression method used by Parsley and Wei (2001, hereafter PW) in their analysis of the border effect. Our result shows that both distance and price stickiness play a significant role in determining the variability of LOP deviations. This empirical finding is robust to changes in the regression specification and alternative measures of relative price volatility. Thus, our theoretical model and empirical results support the conjecture of ER on the importance of integrating models of price stickiness with the new economic geography models of trade.

2 The model

2.1 A benchmark economy

The economy consists of two cities A and B, with mass of households equal to 1/2 each. Both cities are located in the same country. Each city is subject to city-specific shocks, but parameters of preferences and technologies are the same. Households in the two cities hold complete state-contingent money claims. Trade is over a continuum of goods between the two cities. Under monopolistic competition, a continuum of firms set prices to satisfy demand for a particular good in a particular city (pricing to market). Households in each city choose consumption and labor supply over an infinite horizon subject to a cash-in-advance (CIA) constraint.

We consider two levels of constant elasticity of substitution (CES) aggregation. The lower level of aggregation is the brand v of a particular good. Brands of each good produced in city A are indexed by $v \in [0, 1/2]$, while the brands of each good produced in city B are indexed by $v \in (1/2, 1]$. Integrating over brands, we obtain the CES index for consumption of good i in city j, at date t:

$$C_{j,t}(i) = \left[\int C_{j,t}(i,v)^{\frac{\theta-1}{\theta}} dv \right]^{\frac{\theta}{\theta-1}} \text{ for } j = A, B,$$

where $C_{j,t}(i,v)$ is consumption of brand v of good i in city j. The upper level of aggregation is across goods i. The aggregate consumption of city j is:

$$C_{j,t} = \left[\int C_{j,t}(i)^{\frac{\theta-1}{\theta}} di \right]^{\frac{\theta}{\theta-1}}, \text{ for } j = A, B,$$

The elasticity of substitution among goods, θ, is assumed to exceed one.[2]

[2]Allowing for different elasticities between the lower and upper levels of aggregation does not change our main results.

Households

Households in each city maximize the discounted sum of utility subject to an intertemporal budget constraint and a CIA constraint. Households in city j solve

$$\max_{C_{j,t},L_{j,t},M_{j,t},D_{j,t}} \quad \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t (\ln C_{j,t} - L_{j,t}) \tag{1}$$

$$\text{s.t.} \quad M_{j,t} + \mathbb{E}_t(\Upsilon_{t,t+1} D_{j,t+1}) = R_{t-1} W_{j,t-1} L_{j,t-1} + D_{j,t} \tag{2}$$

$$+(M_{j,t-1} - P_{j,t-1} C_{j,t-1}) + T_{j,t} + \Pi_{j,t}$$

$$M_{j,t} \geq P_{j,t} C_{j,t}, \tag{3}$$

for $j = A$ and B. Here, β is the discount factor of households satisfying $0 < \beta < 1$, $\mathbb{E}_t(\cdot)$ is the expectation operator conditional on the information available in period t and $L_{j,t}$ is hours of work supplied by the household in city j.

The left hand side of the intertemporal budget constraint (2) represents the nominal value of total wealth of the household brought into the beginning of period $t+1$. It consists of cash $M_{j,t}$ and one-period state-contingent bonds $D_{j,t+1}$ with nominal stochastic discount factor $\Upsilon_{t,t+1}$. On the right hand side of (2), the household receives nominal labor income $W_{j,t-1}L_{j,t-1}$ from the labor market in city j in period $t-1$ and earns gross nominal interest R_{t-1} per unit of labor income until period t.[3] Also, the household carries nominal bonds in amount $D_{j,t}$ and cash holding remaining after consumption expenditures $(M_{j,t-1} - P_{j,t-1}C_{j,t-1})$ into period t. The aggregate price level, $P_{j,t}$, is given by $P_{j,t} = [\int P_{j,t}(i)^{1-\theta} di]^{\frac{1}{1-\theta}}$, where $P_{j,t}(i)$ is the price index for good i in city j; $P_{j,t}(i)$ is a CES aggregate over differentiated brands: $P_{j,t}(i) = [\int P_{j,t}(i,v)^{1-\theta} dv]^{\frac{1}{1-\theta}}$. Finally, $T_{j,t}$ and $\Pi_{j,t}$ are nominal lump sum transfers from the government and nominal profits of firms operating in city j, respectively.

The first-order conditions in city j are standard:

$$\frac{W_{j,t}}{P_{j,t}} = C_{j,t} \tag{4}$$

$$\Upsilon_{t,t+1} = \beta \left[\left(\frac{C_{j,t+1}}{C_{j,t}} \right)^{-1} \frac{P_{j,t}}{P_{j,t+1}} \right] \tag{5}$$

$$M_{j,t} = P_{j,t} C_{j,t}, \tag{6}$$

for $j = A$ and B. Equation (4) is the intratemporal optimality condition for labor and consumption. Equation (5) represents intertemporal consumption choice between consecutive months. Equation

[3] We assume that the government pays interest rate $R_t(= 1/\mathbb{E}_t \Upsilon_{t,t+1})$ on labor income in period t. This assumption permits households' intra-temporal first-order condition to be undistorted.

(6) means that the CIA constraint always binds. Combining (4) and (6), we obtain

$$M_{j,t} = P_{j,t}C_{j,t} = W_{j,t}, \tag{7}$$

for $j = A$ and B. That is, in each city, the nominal money demand, nominal consumption expenditure and the nominal wage rate are all equal to each other.

Firms

Output is proportional to labor input:

$$Y_{j,t}(i,v) = Z_{j,t}(i)L_{j,t}(i,v),$$

where $Y_{j,t}(i,v)$, $L_{j,t}(i,v)$, and $Z_{j,t}(i)$ denote output, labor demand and exogenous labor productivity. Note that $Z_{j,t}(i)$ is city- and good-specific, following the stochastic process given by:

$$\begin{aligned} \ln Z_{j,t}(i) &= \mu_j^Z(i) + \eta_t + \varepsilon_{j,t}(i) \\ \eta_t &= \eta_{t-1} + \nu_t \qquad \nu_t \sim \text{i.i.d}(0, \sigma_\nu^2) \\ \varepsilon_{j,t}(i) &= \rho\varepsilon_{j,t-1}(i) + \xi_{j,t}(i) \qquad \xi_{j,t}(i) \sim \text{i.i.d.}(0, \sigma_{\xi_j}^2), \end{aligned} \tag{8}$$

where $\mu_j^Z(i)$ is a fixed effect specific to good i and city j, η_t is a stochastic trend common to all goods and both cities and $\varepsilon_{j,t}(i)$ is a persistent idiosyncratic stochastic component, with $|\rho| < 1$.

The output is perishable so that the consumption equals output in the current period:

$$\frac{1}{2}C_{A,t}(i,v) + (1+\tau)\frac{1}{2}C_{B,t}(i,v) = Y_{A,t}(i,v), \tag{9}$$

for $v \in [0, 1/2]$ and

$$(1+\tau)\frac{1}{2}C_{A,t}(i,v) + \frac{1}{2}C_{B,t}(i,v) = Y_{B,t}(i,v), \tag{10}$$

for $v \in (1/2, 1]$. Here τ is an iceberg transportation cost.

Calvo pricing

We introduce nominal rigidities à la Calvo (1983): each period, a randomly selected fraction of firms $1 - \lambda_i$ are allowed to reset prices. As suggested by the subscript on λ_i, the frequency of price changes varies by good i, but not by city j.

Because firms choose the same optimal price when they reset prices, we define the optimal price that firms producing good i in city A charge consumers in city A as $P_{AA,t}(i)$ and the optimal price that firms producing good i in city A charge consumers in city B as $P_{AB,t}(i)$. Thus, the first subscript represents the city of production and the second subscript represents the city of consumption. The price $P_{AA,t}(i)$ solves the following maximization problem:

$$\max_{P_{AA,t}(i)} \mathbb{E}_t \sum_{h=0}^{\infty} \lambda_i^h \Upsilon_{t,t+h} \left[P_{AA,t}(i) - \frac{W_{A,t+h}}{Z_{A,t+h}(i)} \right] \left(\frac{P_{AA,t}(i)}{P_{A,t+h}(i)} \right)^{-\theta} C_{A,t+h}(i). \tag{11}$$

Here, we used the demand function as a constraint on the maximization problem:

$$C_{A,t+h}(i,v) = \left(\frac{P_{AA,t}(i)}{P_{A,t+h}(i)} \right)^{-\theta} C_{A,t+h}(i).$$

On the other hand, $P_{AB,t}(i)$ solves the following maximization problem:

$$\max_{P_{AB,t}(i)} \mathbb{E}_t \sum_{h=0}^{\infty} \lambda_i^h \Upsilon_{t,t+h} \left[P_{AB,t}(i) - (1+\tau) \frac{W_{A,t+h}}{Z_{A,t+h}(i)} \right] \left(\frac{P_{AB,t}(i)}{P_{B,t+h}(i)} \right)^{-\theta} C_{B,t+h}(i), \tag{12}$$

Similarly, the optimal reset prices for firms located in city B, $P_{BA,t}(i)$ and $P_{BB,t}(i)$, solve

$$\max_{P_{BA,t}(i)} \mathbb{E}_t \sum_{h=0}^{\infty} \lambda_i^h \Upsilon_{t,t+h} \left[P_{BA,t}(i) - (1+\tau) \frac{W_{B,t+h}}{Z_{B,t+h}(i)} \right] \left(\frac{P_{BA,t}(i)}{P_{A,t+h}(i)} \right)^{-\theta} C_{A,t+h}(i) \tag{13}$$

and

$$\max_{P_{BB,t}(i)} \mathbb{E}_t \sum_{h=0}^{\infty} \lambda_i^h \Upsilon_{t,t+h} \left[P_{BB,t}(i) - \frac{W_{B,t+h}}{Z_{B,t+h}(i)} \right] \left(\frac{P_{BB,t}(i)}{P_{B,t+h}(i)} \right)^{-\theta} C_{B,t+h}(i). \tag{14}$$

Equilibrium

The monetary authority in this economy controls the growth rate of the money stock such that the money supply given to city j, $M^s_{j,t}$, is exogenous. The market clearing condition for each money market is $M^s_{j,t} = M_{j,t}$ for $j = A$ and B. The log of $M^s_{j,t}$ follows a non-stationary process given by

$$\begin{aligned} \ln M^s_{j,t} &= \mu_j^M + \eta_t^M \\ \Phi(L)\Delta\eta_t^M &= \Psi(L)\nu_t^M, \qquad \nu_t^M \sim \text{i.i.d}(0, \sigma^2_{\nu_M}), \end{aligned} \tag{15}$$

where $\Psi(L)$ and $\Phi(L)$ are arbitrary lag polynomials and μ_j^M is a city-specific parameter. These parameters are determined by the monetary authority. Here we assume that $\Delta\eta_t^M$ follows a stationary ARMA process and that the shock ν_t^M is common to both cities so the growth rate of money supply $\Delta\eta_t^M$ is identical in the two cities.

Transfers from the government to each city equal money injections minus the lump sum taxes from the government paying interest: $T_{j,t} = M^s_{j,t} - M^s_{j,t-1} - (R_{t-1} - 1)W_{j,t-1}L_{j,t-1}$ for $j = A$ and B. The profits of firms in city j accrue exclusively to households in city j: $\Pi_{A,t} = \int_i \int_{v=0}^{\frac{1}{2}} \Pi_{A,t}(i,v)dvdi$

and $\Pi_{B,t} = \int_i \int_{v=\frac{1}{2}}^{1} \Pi_{B,t}(i,v)dvdi$, where $\Pi_{j,t}(i,v)$ is the profit of a firm in city j, producing brand v of good i.

The labor market clearing conditions are

$$\frac{1}{2}L_{A,t} = \int_{i=0}^{1}\left[\int_{v=0}^{\frac{1}{2}} L_{A,t}(i,v)dv\right]di, \qquad \frac{1}{2}L_{B,t} = \int_{i=0}^{1}\left[\int_{v=\frac{1}{2}}^{1} L_{B,t}(i,v)dv\right]di.$$

State-contingent bond markets clear at each date and state: $\frac{1}{2}D_{A,t} + \frac{1}{2}D_{B,t} = 0$.[4] Market clearing conditions for goods were given by (9) and (10) earlier.

An *equilibrium* of this economy is a collection of allocations and prices: (i) $\{C_{A,t}(i,v)\}_{i,v}$, $M_{A,t}$, $D_{A,t}$ and $L_{A,t}$ for households in city A; (ii) $\{C_{B,t}(i,v)\}_{i,v}$, $M_{B,t}$, $D_{B,t}$ and $L_{B,t}$ for households in city B; (iii) $\{P_{A,t}(i,v), P_{B,t}(i,v), L_{A,t}(i,v), Y_{A,t}(i,v)\}_{i,v\in[0,1/2]}$ for firms in city A; (iv) $\{P_{A,t}(i,v), P_{B,t}(i,v), L_{B,t}(i,v), Y_{B,t}(i,v)\}_{i,v\in(1/2,1]}$ for firms in city B; and (v) nominal wages and bond prices satisfy the following conditions: (a) households' allocations solve their maximization problem, (1) - (3); (b) prices and allocations of firms solve their maximization problem (11) - (14); (c) all markets clear; (d) the money supply process and transfers for each city satisfy the specifications described above.

2.2 Characterizing equilibrium dynamics

We now consider the short-run fluctuations of LOP deviations in the benchmark economy. The first-order condition for pricing when the place of production and consumption are the same implies

$$\mathbb{E}_t \sum_{h=0}^{\infty} \lambda_i^h \Upsilon_{t,t+h}\left[P_{jj,t}(i) - \frac{\theta}{\theta-1}\frac{W_{j,t+h}}{Z_{j,t+h}(i)}\right]\left(\frac{P_{jj,t}(i)}{P_{j,t+h}(i)}\right)^{-\theta} C_{j,t+h}(i) = 0. \tag{16}$$

The first-order condition when the place of production and consumption are different implies

$$\mathbb{E}_t \sum_{h=0}^{\infty} \lambda_i^h \Upsilon_{t,t+h}\left[P_{jk,t}(i) - (1+\tau)\frac{\theta}{\theta-1}\frac{W_{j,t+h}}{Z_{j,t+h}(i)}\right]\left(\frac{P_{jk,t}(i)}{P_{k,t+h}(i)}\right)^{-\theta} C_{k,t+h}(i) = 0. \tag{17}$$

Let $\bar{P}_{jk,t}(i) = Z_{j,t}(i)P_{jk,t}(i)/M_{j,t}$ and $\hat{\bar{p}}_{jk,t}(i) = \ln \bar{P}_{jk,t}(i) - \ln \bar{P}_{jk}(i)$ (i.e., the log-deviation of the normalized optimal price from the steady state). Given that $M_{j,t} = W_{j,t}$, we obtain the common log-linearized expression for (16) and (17):

$$\hat{\bar{p}}_{jk,t}(i) = (1-\lambda_i\beta)\mathbb{E}_t \sum_{h=0}^{\infty} (\lambda_i\beta)^h (\hat{g}^M_{j,t+1,t+h} - \hat{g}^Z_{j,t+1,t+h}(i)). \tag{18}$$

[4] Dividing bond markets into city-specific markets is simply redundant because allocations of state-contingent bonds in two cities are indeterminate.

Here $\hat{g}^X_{j,t+1,t+h}(i)$ is given by

$$\hat{g}^X_{j,t+1,t+h}(i) = \begin{cases} 0 & \text{for} \quad h = 0 \\ \sum_{d=1}^{h} \hat{g}^X_{j,t+d}(i) & \text{for} \quad h = 1, 2, \cdots, \end{cases}$$
$$\hat{g}^X_{j,t+d}(i) = \ln(X_{j,t+d}(i)/X_{j,t+d-1}(i)).$$

for $j = A, B$ and $X = M, Z$.

The intuition behind (18) is that firms choose prices according to current and future paths of money and labor productivity growth. Due to time-invariant trade cost (τ), prices in the source and destination markets move in proportion this is why the terms on the right-hand-side of (18) lack k subscripts.

We define $\bar{P}_{j,t}(i)$ as the normalized price index for good i (i.e., $\bar{P}_{j,t}(i) = Z_{j,t}(i)P_{j,t}(i)/M_{j,t}$). We define $\hat{\bar{p}}_{j,t}(i)$ as the log-deviation of $\bar{P}_{j,t}(i)$ from the steady state. Due to Calvo-type price stickiness, the fluctuation in the price index in city A for good i, $\hat{\bar{p}}_{A,t}(i)$, can be written recursively as

$$\begin{aligned} \hat{\bar{p}}_{A,t}(i) = \lambda_i[\hat{\bar{p}}_{A,t-1}(i) + \hat{g}^Z_{A,t}(i) - \hat{g}^M_{A,t}] \\ + (1-\lambda_i)\{S_A(i)\hat{\bar{p}}_{AA,t}(i) + [1 - S_A(i)][\hat{\bar{p}}_{BA,t}(i) + \hat{z}_t(i)]\}, \end{aligned} \tag{19}$$

where $\hat{z}_t(i)$ is the labor productivity differential, between cities A and B, for good i, relative to its unconditional mean (i.e., $\hat{z}_t(i) = [\ln Z_{A,t}(i) - \mu^Z_A(i)] - [\ln Z_{B,t}(i) - \mu^Z_B(i)]$).

The steady-state expenditure share on home brands of good i, for city A, is $S_A(i) = 1/\{1 + (1+\tau)^{1-\theta}\exp[(1-\theta)(\mu_B(i) - \mu_A(i))]\}$. The trade cost plays its usual role here in generating home bias in the consumption of home brands relative to imported brands. Higher trade costs generate greater home bias (driving the share above 0.5).

The elasticity of the home bias with respect to the trade cost is greater the higher is the elasticity of substitution across varieties, θ. The additional channel is the differential of the $\mu_j(i)$ with each term given by $\mu^M_j - \mu^Z_j(i)$. To understand our notation of $\mu_j(i)$, note that $W_{j,t} = M_{j,t}$ in equilibrium. Hence, we can interpret $\mu_j(i)$ as a deterministic component of the log of nominal marginal cost (i.e., $\ln\{W_{j,t}/Z_{j,t}(i)\}$). The cost differential enters as a standard relative price effect on the choice of consumption of the home and imported varieties. That is, if the foreign variety of a particular good is relatively inexpensive to produce due to higher productivity, it may end up constituting a higher share of home consumption of that good than the domestic variety, despite the trade cost.

To understand (19), note that a fraction λ_i of firms are randomly drawn from $[0, 1]$ interval and do not change prices whereas the remaining $1 - \lambda_i$ of firms choose the optimal prices. The expression inside the bracket in the first component of the right-hand side of (19) represents prices charged by firms who do not reset prices and this expression is adjusted for technological and money growth. The expression inside the curly bracket in the second component shows the average newly reset price for good i, which is an expenditure weighted average of $\bar{P}_{AA,t}(i)$ and $\bar{P}_{BA,t}(i)$. For the latter price, we need to adjust by $\hat{z}_t(i)$ to be consistent with the normalization of $\hat{\bar{p}}_{A,t}(i)$. Note that $\hat{\bar{p}}_{A,t}(i)$ is stationary because $\ln Z_{A,t}(i)$ and $\ln Z_{B,t}(i)$ have a common stochastic trend and they are cointegrated. Indeed, due to elimination of a stochastic common trend, $\hat{z}_t(i)$ is actually just $\varepsilon_{A,t}(i) - \varepsilon_{B,t}(i)$.

Similar argument gives the evolution of the price index in city B for good i:

$$\begin{aligned} \hat{\bar{p}}_{B,t}(i) &= \lambda_i[\hat{\bar{p}}_{B,t-1}(i) + \hat{g}^Z_{B,t}(i) - \hat{g}^M_{B,t}] \\ &\quad + (1-\lambda_i)\{S_B(i)\hat{\bar{p}}_{BB,t}(i) + [1 - S_B(i)][\hat{\bar{p}}_{AB,t}(i) - \hat{z}_t(i)]\}, \end{aligned} \tag{20}$$

where $S_B(i) = 1/\{1 + (1+\tau)^{1-\theta}\exp[(1-\theta)(\mu_A(i) - \mu_B(i))]\}$.

Using the definitions of $\hat{\bar{p}}_{j,t}(i)$, we obtain the log-deviation of the relative price in city B to the price in city A,

$$\hat{q}_t(i) = [\hat{\bar{p}}_{B,t}(i) - \hat{\bar{p}}_{A,t}(i)] + \hat{z}_t(i). \tag{21}$$

The presence of $\hat{z}_t(i)$ is basically an implication of the way the raw prices are normalized in the model.

When the productivity differential is i.i.d., $\rho = 0$, Appendix A shows the stochastic process of $\hat{q}_t(i)$ is:

$$\hat{q}_t(i) = \lambda_i \hat{q}_{t-1}(i) + (1-\lambda_i)(1-\lambda_i\beta)(S_A(i) + S_B(i) - 1)\hat{z}_t(i). \tag{22}$$

Our focus is the volatility of intra-national LOP deviations and its relationships to price stickiness, λ_i and transportation costs τ. Transport cost increases drive $S_A(i) + S_B(i)$ above 1 (this is for the case of common steady-state productivity levels) so that the term multiplying the shock becomes a larger positive number, increasing the variance of the LOP deviations.

In our empirical work, a battery of alternative volatility measures are used: (i) the standard deviation of the one-month first difference, $std(\Delta q(i)) = \sqrt{\mathbb{E}[\Delta\hat{q}_t(i)]^2}$; (ii) the standard deviation of the quasi-difference, $std(\Delta_\lambda q(i)) = \sqrt{\mathbb{E}[\hat{q}_t(i) - \lambda_i\hat{q}_{t-1}(i)]^2}$; (iii) the standard deviation of the non-filtered series (level), $std(q(i)) = \sqrt{\mathbb{E}[\hat{q}_t(i)]^2}$. The next proposition establishes the key implication of our model, which is valid for all of these transformations of the LOP deviation.

Proposition 1. *Under the preference* $\ln C_{jt} - L_{jt}$*, CIA constraints, technology shock specified by* (8)*, the exogenous money growth rates specified by* (15)*, and good-specific Calvo pricing,* $std(\Delta q(i))$*,*

$std(\Delta_\lambda q(i))$ and $std(q(i))$ decrease with price stickiness λ_i and increase with an iceberg transportation cost τ.

Proof. See Appendix A. $\square$

The intuition behind this proposition is as follows. Consider the role of price rigidity in the case when $\rho = 0$. The variance of the quasi-difference is clearly falling in the extent of price stickiness because the shock is pre-multiplied by $(1 - \lambda_i)(1 - \lambda_i\beta)$; this is approximately equal to $(1 - \lambda_i)^2$ since $\beta = 0.99$ in monthly data(see equation (23)). Thus the impact of the shock is rapidly damped as λ_i moves toward 1 since the coefficient on the shock goes to zero. This effect on the innovation component to the $\hat{q}_t(i)$ process is always present. The unconditional variance is more subtle since for the level of $\hat{q}_t(i)$, persistence is rising in price stickiness which counteracts the reduction in the innovation variance noted above. However, the offset is less than one-for-one so long as $\lambda_i < 1$. The Appendix shows this result as well as the case of first-differencing. The bottom line is that shocks tend not to pass-through to nominal prices under a sticky-price scenario, even though the persistence rises.

Turning to the trade cost, notice that $S_j(i)$ is strictly increasing in τ for all i and j. That is, a higher trade cost leads to more home bias in expenditure, pushing both $S_A(i)$ and $S_B(i)$ upward (and therefore doing the same for their sum). Thus, a productivity shock in the production of the home varieties of good i, while lowering the relative price of home varieties in both markets (for price adjusters), carries a larger (lower) weight in home (foreign) consumption and thus results in an asymmetric price index adjustment of that good, across cities, and more relative price (i.e. LOP) variation.

2.3 Implications of price stickiness for intra-national LOP deviations

This sub-section discusses the role of price stickiness on the volatility of LOP deviations across *intra-national* and *international* contexts.

Kehoe and Midrigan (2007) argue that volatility and price stickiness should be positively correlated in the international context. In contrast, our model predicts that they are negatively correlated in the intra-national context. Why does this difference arise?

Recall, equation (23), provides the dynamics of LOP deviations in our model:

$$\hat{q}_t(i) = \lambda_i \hat{q}_{t-1}(i) + (1 - \lambda_i)(1 - \lambda_i\beta)(S_A(i) + S_B(i) - 1)\hat{z}_t(i). \tag{23}$$

where $\hat{z}_t(i)$ is the relative labor productivity shock.

On the other hand, the Calvo pricing model used by Kehoe and Midrigan (2007), under the same preference and constraints as ours, but in the absence of labor productivity shocks, implies international relative prices follow an AR(1) process of the form:

$$\hat{q}_t(i) = \lambda_i \hat{q}_{t-1}(i) + \lambda_i \Delta \hat{s}_t, \tag{24}$$

where $\hat{q}_t(i) = \hat{s}_t + \hat{p}_t^*(i) - \hat{p}_t(i)$ and $\hat{p}_t(i)$ ($\hat{p}_t^*(i)$) equals the domestic (foreign) log price index for good i. The logarithm of the nominal exchange rate is $\hat{s}_t$, which Kehoe and Midrigan (2007) assume is a random walk.

The cities of Japan share a common monetary shock. While they do not share a common productivity shock, in general, the productivity shock does not alter relative price of non-adjusters, by definition. Thus sticky prices lead to more stable prices. Moreover, the LOP deviation across adjusting firms only changes if there is a demand asymmetry (induced by either trade costs or a long-run productivity asymmetry). This is because the increased supply in one location would have a symmetric impact on price indices in both cities in the absence of a demand asymmetry (i.e., when $S_A(i) + S_B(i) - 1 = 0$).

In the Kehoe-Midrigan model, the cross-border relative price for non-adjusters moves one-for-one with the nominal exchange rate shock, as evident in the definition of the LOP deviation. This is where the correlation of real and nominal exchange rates is perfect. It is the firms that adjust prices in response to the nominal exchange rate that mitigate the overall impact of price rigidities on the LOP deviation. As the frequency of price adjustment falls, the former effect dominates and LOP variability increases.

Figure 1 uses (23) to generate two simulated paths of LOP deviations for the intra-national case under different values of λ_i.[5] The figure shows that stickier prices ($\lambda_i = 0.98$) result in much less volatile fluctuations compared to more flexible prices ($\lambda_i = 0.85$). When prices are sticky, they do not adjust in any of the cities, so the LOP movements look nothing like the productivity movements.

Figure 2 uses (24) to generate two simulated paths of LOP deviations for the international case.[6] In contrast to the intra-national case, stickier prices ($\lambda_i = 0.98$) generate *more* volatile fluctuations than the more flexible price case ($\lambda_i = 0.50$). When prices are sticky in local currency units, the

[5] We set $\tau = 0.05$, $\mu_A(i) = \mu_B(i)$, $\beta = 0.96^{\frac{1}{12}}$, $\theta = 11$, and $\hat{z}_t \sim N(0, 0.05^2)$ for this simulation.

[6] To simulate the theoretical time series, we assume that $\hat{s}_t = \hat{s}_{t-1} + \omega_t$, where $\omega_t \sim N(0, 0.05^2)$.

real exchange rate tends to track the nominal exchange rate and the real exchange rate and the nominal exchange rate shock share similar stochastic properties.

Figures 3 and 4 also confirm that this contrast is preserved under differenced series $\Delta\hat{q}_t(i)$. These comparisons tell us that the intra-national setting is useful in isolating the effect of sticky prices. In the international model, real exchange rates are volatile with flexible prices in the presence of productivity shocks or with sticky prices in the presence of nominal exchange rate shocks. In the intranational model, the real exchange rate is volatile under flexible prices and stable under sticky prices. Thus, the intranational context helps us to isolate the role of sticky prices by not muddling real and nominal shocks, which have opposite effects on volatility under local currency pricing.

3 Data

3.1 Retail price survey

The price data is from the *Retail Price Survey* published by Ministry of Internal Affairs and Communications (MIAC) in Japan.[7] Every month, the survey collects retail price observations from outlets in town and cities; it provides the basic data used to construct Japan's Consumer Price Index. The surveyed items (i.e., goods and services) cover most of the items in the household consumption basket. For many goods, prices are available in several specifications based on the quality of the product, the quantity sold in a package and other characteristics.

In terms of locations, our dataset covers all cities with prefectural government and cities with population of 150,000 or more (71 cities). The sample period of our dataset is from January 2000 to December 2006. The number of goods surveyed exceeds 600, though it varies over time due to missing observations. Most specifications of goods and services appear consistently over our sample period, but some are added into or dropped from the sample because MIAC changes the surveyed items based on changing household consumption patterns.[8]

MIAC surveys retail prices of each good, maintaining a fixed set of survey outlets, to the extent possible. The number of outlets that MIAC surveys in each sample district depends on the population size of districts and the classification of items. For example, while food prices in cities with prefectural government are surveyed from four outlets, those in Tokyo metropolitan area are

[7] The previous studies on LOP in Japan often use this data source. Examples include PW, Baba (2007), Choi and Matsubara (2007), and Cheung and Fujii (2008).

[8] For example, printer for personal computers and DVD software are only added recently, in 2003 and 2005, respectively.

surveyed from 42 outlets. In contrast, public utility charges such as water charges are surveyed from only one outlet in both districts because the price is considered to be almost uniform within each district. When more than one outlet is surveyed, MIAC takes the simple arithmetic mean of these prices and this is the published data we have available for use in this study.

3.2 Intra-national LOP deviations

The LOP deviation, $q_{j,t}(i)$, is measured as the log of the relative price of good i in city j to the price of the same good in the Tokyo metropolitan area.[9]

$$q_{j,t}(i) = \ln P_{j,t}(i) - \ln P_{Tokyo,t}(i),$$

for $j = 1, 2, ...n$ and n is the number of cities (excluding Tokyo). In the model, $P_{j,t}(i)$ and $P_{Tokyo,t}(i)$ are price indices rather than the prices of individual brands. When MIAC computes the arithmetic mean of prices, more outlets are surveyed in Tokyo metropolitan area and cities with prefectural governments than cities without prefectural governments. Since we are interested in the relative price index, we treat the arithmetic mean of a survey price as the price index for that good.[10] To ensure the averages are computed over a sufficient number of outlets, we restrict the cities to those with prefecture governments. This reduces the number of relative prices to 46, because there are 47 prefectural governments in Japan, including Tokyo.

We also drop the relative price data where the number of the observations for each of the three filtered time series $q_{j,t}(i)$ is less than 48 months. With this sample selection, the number of observations are 17,797 for one-month differenced and quasi-differenced series and 21,926 for non-filtered series. While our dataset has information on more than 600 goods, our sample selection reduces the number of goods to 389 for differenced series and to 489 for raw series.

3.3 Frequency of price adjustment

Let f_i be the ratio of the number of months in which prices changed for good i to the total number of the months available in the sample for that good. The standard method of measuring price stickiness is to set $\lambda_i = 1 - f_i$. This measure is problematic in our setting because the number of outlets surveyed is positively related to the size of the city in which the survey is conducted. Since

[9] Our results are robust to the use of Tokushima, the approximate geographic center of Japan, as an alternative numeraire city.

[10] Admittedly, a caveat is that MIAC does not take a geometric mean as the theory does.

the published data we work with is an average price across the city, the measured fraction, f_i, will tend to be larger in larger cities partly as an artifact of the different timing of price changes across outlets within the city.

To mitigate this bias, we use the information on the number of outlets surveyed in each city, which is provided by MIAC's publication, *Outline of the Retail Price Survey*.[11] We categorize city-by-city outlet variation across 24 item groups. For example, foods and alcoholic beverages belong to the same item group. In this particular item group, MIAC surveys the retail prices from 42, 12, 8, and 4 outlets depending on city population.

Based on the information on outlet variation, we measure (city-by-city) price stickiness by $(1-f_i)^{\frac{1}{r}}$ where r is the number of outlets. To see how this works to mitigate the bias, suppose that MIAC collects price data in a city from two outlets over the sample period. Under the Calvo-type price stickiness assumption, price changes are independent across outlets and occur with probability $1-\lambda_i$. If no change in the arithmetic mean is observed at a point of time, it suggests that both prices remained constant. Because the probability is λ_i^2, the probability that a change in the arithmetic mean occurs, f_i, becomes $1-\lambda_i^2$. Consequently, $\lambda_i = (1-f_i)^{\frac{1}{2}}$. Similarly, if MIAC collects price data from 42 outlets as in food items, our measure of price stickiness is $(1-f_i)^{\frac{1}{42}}$ in such a case. This computation varies city-by-city and good-by-good, depending on the population size of cities and item groups.

To obtain good-specific price stickiness for each good, we take the simple arithmetic mean of city-by-city probabilities of no price adjustment computed by the method above. This method critically depends on the Calvo-type price stickiness assumption that price changes occurs independently over time. Thus, the measured price stickiness might be too high if price changes are synchronized across outlets within the city. To mitigate the problem of synchronization, we use all available retail price data from 71 cities including the ones where the number of outlets are relatively small, instead of limiting the sample to 47 cities with prefectural government.

Nakamura and Steinsson (2008) and Klenow and Kryvtsov (2008) highlight the importance of considering the effect of sales and product substitutions in the measurement of price stickiness. In *the Retail Price Survey*, MIAC does not collect sale prices and asks retailers to report regular prices instead.[12] In contrast, MIAC does not explicitly adjust product substitutions or changes in retail

[11] It is available at `http://www.stat.go.jp/english/data/kouri/pdf/outline.pdf`.

[12] In particular, MIAC defines sales as temporary price decrease which are continually observed for less than seven days.

prices stemming from changes in detailed specifications. Though we admit the presence of product substitutions may lead us to understate price stickiness, we define regular price changes as price changes including product substitutions.

Table 1 summarizes our findings on price stickiness for categories of goods between January 2000 and December 2006. According to our method, the median frequency of price change is about 8.8 percent per month and the implied duration is 11.3 months for all goods. Our median estimate is lower than the value reported by Higo and Saita (2007) who measure the frequency of price changes in Japan between 1989 and 2003. They find that the annual average of frequencies ranges from about 18 to 24 percent. Our results imply that the degree of price stickiness in Japan is higher than the existing literature suggests.[13]

As Table 1 shows, we observe enormous heterogeneity in the infrequency of price changes across groups. This high degree of heterogeneity is also found in Higo and Saita (2007). In the extreme case of transportation, prices remain fixed with probability 0.99.[14] At the opposite extreme case, prices of women's apparel are much less rigid.[15]

The last column of Table 1 reports the medians of the unconditional standard deviation for $q_{j,t}(i)$ by group. LOP volatility tend to be large when λ_i is low. For example, the categories with the three highest standard deviations (food at home, household furnishings and operations and men's and boy's apparel) are among the lowest four categories in terms of their corresponding λ_i. Transportations and fuel and other utilities lie at the other end of the distribution with low volatility and high price rigidity.

4 The regressions

4.1 Main regression results

Our regressions are designed to evaluate the role of price stickiness and trade cost in explaining the volatility of $q_{j,t}(i)$. We follow ER in hypothesizing the volatility of the prices of similar goods

[13]It should be noted that Higo and Saita (2007) also try to mitigate the problem we address. In particular, they limit the number of the sample districts to 55 cities and do not use any retail price data in the largest cities of Japan. By eliminating price data in large cities, the number of outlets reduces to at most four in their data.

[14]The inflexibility of prices for this category may partly reflect the absence of airline fares.

[15]This high frequency could arise from product substitutions that MIAC does not explicitly consider. Nakamura and Steinsson (2008) have argued that the effect of product substitution on the regular price of apparel is large in relative to other groups.

sold in different locations is related to the distance between the locations and other explanatory variables. The main difference between the regressions of ER and our intra-national LOP regressions is that the key explanatory variable, namely, their dummy variable for crossing a national border, is replaced by a variable of price stickiness specific to each product but common to all cities.

The baseline regression is,

$$V(q_{ij}) = \beta_1 \ln(dist_j) + \beta_2 \lambda_i + \sum_{k=1}^{n} \gamma_k D_{kj}^C + u_{ij} \tag{25}$$

Note that this is a pooled regression using all goods $i = 1, ..., m$ and cities $j = 1, ..., n$, with a restriction $\sum_{k=1}^{n} \gamma_k = 0$, where $dist_j$ is the greater-circle distance between two locations, namely city j and Tokyo (the benchmark city), λ_i is price stickiness for a good i, D_{kj}^C is a city-pair dummy variable which takes on a value of one when $k = j$, and u_{ij} is the regression error.

ER measure LOP volatility as the standard deviation of either: i) the differenced series; or ii) the AR filtered series of the log of the relative price.[16] They also check robustness of their results using the 10-90th percentile range, defined as the spread between the 10th and 90th percentiles. PW examine the standard deviation of the first differenced series and the inter-quartile range, defined as the spread between 25th and 75th percentiles, of the first differenced series.

We measure LOP volatility using both the standard deviation and the inter-quartile ranges for each of the following transformations of the data: (i) one-month first differenced series, $\Delta q_{j,t}(i) = q_{j,t}(i) - q_{j,t-1}(i)$; (ii) quasi-differenced series; $\Delta_\lambda q_{j,t}(i) = q_{j,t}(i) - \lambda_i q_{j,t-1}(i)$; and (iii) the raw series, $q_{j,t}(i)$.

Distance is used as a proxy for unobserved trade costs. As in the ER regression and the standard gravity model of trade, we take log of distance to impose a concave relationship between relative price volatility and distance. Since trade costs are expected to rise with distance, the theory predicts a positive coefficient on distance ($\beta_1 > 0$). The coefficient on the price stickiness parameter, λ_i, is predicted to be negative ($\beta_2 < 0$).

Table 2 reports our regression results using three real exchange rate measures and two volatility metrics. In all six cases, both β_1 and β_2 are of the hypothesized sign and highly significant based on heteroskedasticity-consistent standard errors reported below the point estimates.[17] Explanatory

[16] To be more specific, ER take the two-month difference because some prices were only reported every other month. For the AR filtered measure, two-month-ahead in-sample forecast error from the regression of price on six lags and seasonal dummies is used.

[17] We also ran regressions where city-pair dummies are replaced with a constant term for robustness. Our analysis revealed that the signs of β_1 and β_2 remain unaltered.

power is generally very good when volatilities are computed for the first differenced or quasi-differenced series.

Note that our approach is similar to PW in running a two-way cross-sectional regression by pooling all goods and cities, which extends the one-way cross-sectional analysis of ER who pooled locations, but not goods. When the standard deviation is used as the volatility measure for the first differenced series, the regression fit is very close to that of PW in terms of the adjusted R^2. When inter-quartile range is used, the adjusted R^2 becomes as high as 73 percent, higher than PW. Similar coefficients of determination are obtained for the quasi-differenced series.

Significantly positive estimates of β_1 confirm the importance of distance in explaining the intra-national relative price dispersion. On the whole, the distance effects measured by the point estimates are somewhat larger in magnitude than the values previously reported. In particular, our point estimate of 0.035 for the case of standard deviation of differenced series, is much higher than estimates using international data and moderately higher than estimates using intra-national data. For example, ER report that the estimate of β_1 is 0.001 for the US-Canadian cities and PW find that it is 0.005 for the US-Japanese cities. On the other hand, Parsley and Wei's (1996) intra-national estimates range between 0.004 - 0.018 for the US cities and Ceglowski's (2003) estimate is 0.018 for the Canadian cities.

Significantly negative estimates of β_2 imply that, holding distance constant, volatility is lower for goods with less frequent price adjustments. Our interest is in line with that of ER who examined the role of the nominal price stickiness in accounting for a part of the border effect. The problem we noted earlier, however, is that real and nominal shocks have opposite effects on LOP volatility in the presence of sticky prices for cross-border pairs, such as studied by ER. Isolating the exercise to intranational analysis while measuring price stickiness directly circumvents this problem.

4.2 The distance equivalent of price stickiness

Using the estimated coefficients in the volatility regression on distance and border dummy, ER claim that crossing the US-Canada border is equivalent to an intranational distance of 75,000 miles. PW recommend using a modification to ER estimates so that the results would be unaffected by a change in the unit of distance measurement (e.g., changes from miles to kilometers). They show that their modification results in much higher implied distance than the ER estimates. Here, we ask how much extra distance, δ, do we need to add to an initial distance level $dist_0$ to match the increased LOP variability associated with an increase in price stickiness of 0.01 from an initial level of λ_0. This distance equivalent of the price stickiness change can be obtained by solving

$$\beta_1 \ln(dist_0) + \beta_2\lambda_0 = \beta_1 \ln(dist_0 + \delta) + \beta_2(\lambda_0 + 0.01)$$

where β_1 and β_2 are coefficients in the regression model (25). Solving the equation for the increment to distance, δ, yields

$$\delta = dist_0 \times \{\exp(-(\beta_2/\beta_1) \times 0.01) - 1\}$$

for a 0.01 increment starting from λ_0.

Substituting the estimates of β_1 and β_2 from Table 2 for the first differenced series, we obtain the implied distance growth of 5 percent when the standard deviation is used, and 6 percent when inter-quartile range is used. Note that the formula is valid for any benchmark distance level $dist_0$.

Using the average distance between the cities of 284 miles (456 kilometers), implied distance equivalent is 15 miles (24 kilometers) when the standard deviation is used and 17 miles (27 kilometers) when the inter-quartile range is used. The other two measures of relative price variability yield similar distance equivalence.

Our implied distance growth for each percentage point can be also used to evaluate the effect of introducing price stickiness to a hypothetical flexible price economy. When the price stickiness increases from $\lambda_0 = 0$ (complete price flexibility) to an observed median of 0.91, the average distance of 284 miles needs to be increased to about 27,500 miles, exceeding the circumference of the earth.[18] In this sense, the role of price stickiness in explaining intra-national LOP deviations may be as important as that of the border effect in explaining the international LOP deviations.

4.3 Robustness

Good-specific distance effect

The specification employed in (25) is appropriate when all goods have a common distance effect in the sense that the rate of price change increases at the rate proportional to the growth in distance. Here we consider the case when the coefficient on distance depends on the good. The heterogeneity of the coefficient on distance is expected since transport costs vary across goods with different characteristics (such as their weight, physical volume or cost per unit). Our second specification of the regression model takes the form:

$$V(q_{ij}) = \left\{\beta_1 + \sum_{\ell=1}^{m} \beta_{1\ell} D_{\ell i}^{G}\right\} \ln(dist_j) + \beta_2\lambda_i + \sum_{k=1}^{n} \gamma_k D_{kj}^{C} + u_{ij}$$

[18] For this case, our implied distance of price stickiness can be calculated as $284 \times (1.052)^{91}$ miles.

with the restriction $\sum_{\ell=1}^{m} \beta_{1\ell} = 0$, where $D_{\ell i}^{G}$ is a good-specific dummy variable which takes one when $\ell = i$.

Table 3 reports the results from this regression using all volatility measures and relative price series. We reconfirm that relative price volatility increases with distance and decreases with price stickiness. For all cases, signs of estimated coefficients are the same as predicted by the theory and estimates are statistically significant. Importantly, the regression fit of each case is significantly improved from corresponding results in Table 2. Even for the raw series, adjusted R^2 with the standard deviation used as a volatility measure has now become comparable to that of PW.

On the whole, the estimates of the average distance effect β_1 become somewhat smaller than the estimates of β_1 in equation (25). For example, the value of 0.021 for the specification using the standard deviation of differenced series is now similar to 0.018, the value obtained by Parsley and Wei (1996) and Ceglowski (2003). However, since drops in the value are also observed for the estimates of β_2, the implied distant equivalent of the price stickiness remains about the same as before.

Finally, Figures 5 and 6 show the empirical distributions of $\beta_1 + \beta_{1\ell}$ based on standard deviation and inter-quartile range of the first differenced series, respectively. While some good-by-good variation of the distance effect are observed, they are all positive and tightly distributed around the average value β_1.

Effect of volatility of labor productivity

Both the benchmark and extended specifications above implicitly assumed that volatility of the cross-city labor productivity difference is the same for all city-pairs and among all goods. However, when the volatility of labor productivity differs across cities and goods, this has implications for LOP volatility as well. Goods and cities with unusually high productivity variation are predicted to have higher LOP variation. For this reason, it is desirable to control for the volatility of the labor productivity differential in the regression equation.

Because data on labor productivity specific to both the city and the good is not available, we focus on the city-specific component and run the following two specifications:

$$
\begin{aligned}
V(q_{ij}) &= \beta_1 \ln(dist_j) + \beta_2 \lambda_i + \beta_3 \sigma_j + \alpha + u_{ij} \\
V(q_{ij}) &= \left\{ \beta_1 + \sum_{\ell=1}^{m} \beta_{1\ell} D_{\ell i}^{G} \right\} \ln(dist_j) + \beta_2 \lambda_i + \beta_3 \sigma_j + \alpha + u_{ij},
\end{aligned}
$$

where α is a constant term and σ_j is the time-series standard deviation of the labor productivity difference between Tokyo and the prefecture to which city j belongs in one-to-one correspondence.[19] Note that the new regressions exclude the city-pair dummy and include a constant because adding σ_j to the regression leads to a co-linearity with a city-pair dummy variable. The second equation includes the good-specific distance effect we discussed earlier.

Tables 4 and 5 report the regression results for the above specifications. All signs of the estimates on distance and price stickiness are consistent with the theory and statistically different from zero. The standard deviation of the labor productivity differential, σ_j, is estimated to be positively correlated with relative price volatility though it is imprecisely estimated when we use the first-differenced series.

In these specifications, the estimates of β_1 fall in magnitude and are now comparable to those estimated by ER and PW. This implies that the implied distance equivalent of price stickiness becomes greater. Using the formula of the implied distance equivalent to one percentage point increase in price stickiness, it increases from 15 miles (24 kilometers) to 393 miles (632 kilometers) when the standard deviation of the filtered series of the relative price is used. The implied distance equivalent again suggests an important role of price stickiness in explaining intra-national LOP deviations.

Category-by-category regressions

So far, effects of distance and price stickiness are evaluated by pooling all goods in a single regression. Unlike ER who run good-by-good regressions (using sub-aggregates) in their evaluation of the border effect, we cannot estimate the effect of price stickiness for each good since price stickiness of a good is assumed to be identical for all the cities. However, we can still investigate more detailed effect of price stickiness by running a regression pooling the goods from a group sharing similar good characteristics. Here we use 13 categories of goods described in Table 1. The idea is that such category-by-category regressions allow variations in the coefficients which may perhaps stem from different stochastic processes of technological difference among categories of goods.

Table 6 reports the regression results for each of the 13 good categories, without good-specific distance effects in the specification. In order to conserve space, we only report the results for the

[19] To compute labor productivity, we use annually sampled prefecture-by-prefecture real GDP and the number of workers which are available from the website of Economic and Social Research Institute in the government of Japan. Total hours are computed by multiplying the number of workers by annual hours of work available in *Monthly Labor Survey* published by the Ministry of Health, Labor and Welfare of Japan. Prefecture-by-prefecture labor productivity is then obtained as the real GDP divided by the total hours. The sample period is from 1980 to 2005.

first differenced series with city-pair dummies. Similar results are obtained by using two other price series or by introducing city-specific volatility of technological difference. Note that our categorization of goods closely matches the sub-indices used in ER, thus making it convenient to compare our values to theirs.

When ER run the regression of LOP variability on distance for each of the 14 sub-indices separately using only US cities and only Canadian cities, positive coefficient estimates are obtained for 12 of 14 sub-indices in the US and for all 14 sub-indices in Canada. The number of sub-indices with significantly positive estimates are 8 and 13, respectively for the US and Canada. In contrast, our results yield the correct (hypothesized) sign for cases. The coefficients are also statistically significant with the exception of the standard deviation metric for one out of 13 good categories. As in ER, the explanatory power varies greatly across categories of goods and there are a few categories with a very low adjusted R^2.

Lastly, Table 7 reports the case when good-specific distance effects are allowed in the specification. As in the case of the previous regression results pooling all goods, significant improvement in the regression fit is obtained by introducing the good-specific distance effect. However, with this specification, the number of good categories with coefficients with correct sign is reduced to 11 of 13 categories for standard deviations, and 12 of 13 categories for inter-quartile range. When the sign is wrong, however, the coefficients are not significantly different from zero for all cases.

5 Conclusions

The fact that the aggregate real exchange rate, or the average of the good-level real exchange rates tracks the nominal exchange rate closely is often considered indirect evidence on the importance of price stickiness in generating high volatility of the Law of One Price deviations. Engel and Rogers (1996) also point out that some of the border effects are accounted for by sticky prices. We investigate the role of price stickiness in explaining the volatility of Law of One Price deviations when cities are located in the same country. Focusing on the intra-national dimension is advantageous in extracting the pure effect of price stickiness after eliminating the effect of international trade barriers or nominal exchange rate fluctuations. Using a simple general equilibrium model, we show that the direction of the effect will be opposite in the intra-national context – price stickiness reduces the volatility of good-level real exchange rate. We empirically evaluate the prediction of the model using the micro data of more than 350 highly disaggregated individual good prices from

47 cities in Japan.

The main finding of our empirical analysis is that both distance and the price stickiness matter for intra-national relative price variability. To evaluate the importance of the price stickiness, we also provide a computationally simple measure, namely the distance equivalent of the price stickiness. In the benchmark specification, reduction of price stickiness by a one percentage point is equivalent to 5 to 6 percent increase in distance between cities in generating the same amount of increased volatility. Using the average distance among Japanese cities in our sample, it corresponds to an addition of 15 to 17 miles. We conclude that an approach of integrating the nominal price stickiness features and the framework of new economic geography models of trade is promising in understanding the mechanism of the relative price movements.

Appendix A Derivation for (23) and proof of Proposition 1

In this appendix, we derive (23) and prove Proposition 1. First, consider $\hat{\hat{p}}_{jk,t}(i)$:

$$\begin{aligned}\hat{\hat{p}}_{jk,t}(i) &= (1-\lambda_i\beta)\mathbb{E}_t\sum_{h=0}^{\infty}(\lambda_i\beta)^h[\hat{g}^M_{j,t+1,t+h} - \hat{g}^Z_{j,t+1,t+h}(i)] \\ &= (1-\lambda_i\beta)\mathbb{E}_t\sum_{h=1}^{\infty}(\lambda_i\beta)^h[\hat{g}^M_{j,t+1,t+h} - \hat{g}^Z_{j,t+1,t+h}(i)],\end{aligned}$$

because $g^M_{j,t+1,t+h} = 0$ and $g^Z_{j,t+1,t+h}(i) = 0$ for $h = 0$. Focusing on the second term inside the bracket, we obtain

$$\begin{aligned}&(1-\lambda_i\beta)(\lambda_i\beta)\mathbb{E}_t[\hat{g}^Z_{j,t+1,t+1}(i) + (\lambda_i\beta)\hat{g}^Z_{j,t+1,t+2}(i) + (\lambda_i\beta)^2\hat{g}^Z_{j,t+1,t+3}(i) + \cdots] \\ =\ &(1-\lambda_i\beta)(\lambda_i\beta)\mathbb{E}_t[\hat{g}^Z_{j,t+1}(i) \\ &\qquad + (\lambda_i\beta)(\hat{g}^Z_{j,t+1}(i) + \hat{g}^Z_{j,t+2}(i)) \\ &\qquad + (\lambda_i\beta)^2(\hat{g}^Z_{j,t+1}(i) + \hat{g}^Z_{j,t+2}(i) + \hat{g}^Z_{j,t+3}(i)) + \cdots].\end{aligned}$$

Noting that $\hat{g}^Z_{j,t+d+1}(i) = \nu_{t+d+1} + \varepsilon_{j,t+d+1}(i) - \varepsilon_{j,t+d}(i)$, we obtain

$$\mathbb{E}_t(\hat{g}^Z_{j,t+d+1}(i)) = \rho^d(\rho-1)\varepsilon_{j,t}(i).$$

Therefore,

$$\begin{aligned}\hat{\hat{p}}_{jk,t}(i) = (1-\lambda_i\beta)\mathbb{E}_t\sum_{h=1}^{\infty}(\lambda_i\beta)^h[\hat{g}^M_{j,t+1,t+h}] + (1-\lambda_i\beta)(\lambda_i\beta)(1-\rho) \\ \times\left[\varepsilon_{j,t}(i) + (\lambda_i\beta)\varepsilon_{j,t}(i) + (\lambda_i\beta)\rho\varepsilon_{j,t}(i) + (\lambda_i\beta)^2\varepsilon_{j,t}(i) + (\lambda_i\beta)^2\rho\varepsilon_{j,t}(i) + (\lambda_i\beta)^2\rho^2\varepsilon_{j,t}(i) + \cdots\right].\end{aligned}$$

Arranging terms yields

$$\begin{aligned}\hat{\hat{p}}_{jk,t}(i) &= (1-\lambda_i\beta)\mathbb{E}_t\sum_{h=1}^{\infty}(\lambda_i\beta)^h[\hat{g}^M_{j,t+1,t+h}] + (1-\lambda_i\beta)(\lambda_i\beta)(1-\rho)\\ &\quad\times[(1+\lambda_i\beta+(\lambda_i\beta)^2\cdots)+\lambda_i\beta\rho(1+\lambda_i\beta+(\lambda_i\beta)^2\cdots)+(\lambda_i\beta\rho)^2(1+\lambda_i\beta+(\lambda_i\beta)^2\cdots)+\cdots]\varepsilon_{j,t}(i)\\ &= (1-\lambda_i\beta)\mathbb{E}_t\sum_{h=1}^{\infty}(\lambda_i\beta)^h[\hat{g}^M_{j,t+1,t+h}] + \lambda_i\beta(1-\rho)(1+\lambda_i\beta\rho+(\lambda_i\beta\rho)^2+\cdots)\varepsilon_{j,t}(i).\end{aligned}$$

Hence,

$$\hat{\hat{p}}_{jk,t}(i) = (1-\lambda_i\beta)\mathbb{E}_t\sum_{h=1}^{\infty}(\lambda_i\beta)^h[\hat{g}^M_{j,t+1,t+h}] + \frac{\lambda_i\beta(1-\rho)}{1-\lambda_i\beta\rho}\varepsilon_{j,t}(i). \tag{A1}$$

Next, we subtract (19) from (20). Noting that $\hat{g}^Z_B(i)-\hat{g}^Z_A(i) = -\hat{z}_t(i)+\hat{z}_{t-1}(i)$ and $\hat{g}^M_A = \hat{g}^M_B$ for all t and using (A1), we obtain

$$\begin{aligned}[\hat{\hat{p}}_{B,t}(i)-\hat{\hat{p}}_{A,t}(i)] &= \lambda_i[\hat{\hat{p}}_{B,t-1}(i)-\hat{\hat{p}}_{A,t-1}(i)-\hat{z}_t(i)+\hat{z}_{t-1}(i)]\\ &\quad-\frac{(1-\lambda_i)\lambda_i\beta(1-\rho)}{1-\lambda_i\beta\rho}[S_A(i)+S_B(i)-1]\hat{z}_t(i)\\ &\quad+(1-\lambda_i)(S_A(i)+S_B(i)-2)\hat{z}_t(i).\end{aligned}$$

Combining the relative price equation given by (21) with the above equation, we have

$$\begin{aligned}\hat{q}_t(i) &= \lambda_i\hat{q}_{t-1}(i)+(S_A(i)+S_B(i)-1)(1-\lambda_i)\left[1-\frac{\lambda_i\beta(1-\rho)}{1-\lambda_i\beta\rho}\right]\hat{z}_t(i)\\ &= \lambda_i\hat{q}_{t-1}(i)+(S_A(i)+S_B(i)-1)\frac{(1-\lambda_i)(1-\lambda_i\beta)}{1-\lambda_i\beta\rho}\hat{z}_t(i),\end{aligned} \tag{A2}$$

from which one can prove (23) by setting $\rho = 0$.

Next, we show

$$S_A(i)+S_B(i) > 1,$$

for any $\tau > 0$ and any $\mu(i)$ defined as $\mu(i) = \mu_B(i)-\mu_A(i)$. First, because both $S_A(i)$ and $S_B(i)$ is strictly increasing in τ under $\theta > 1$, it suffices to show $\lim_{\tau\to 0}(S_A(i)+S_B(i)) \geq 1$. From the definition of $S_A(i)$ and $S_B(i)$,

$$\lim_{\tau\to 0}[S_A(i)+S_B(i)] = \frac{1}{1+\exp[(1-\theta)\mu(i)]}+\frac{\exp[(1-\theta)\mu(i)]}{1+\exp[(1-\theta)\mu(i)]} = 1.$$

Second, one can show that $S_A(i)+S_B(i)$ is increasing in $\mu(i) < 0$ and decreasing in $\mu(i) > 0$. Also, by symmetry between $S_A(i)$ and $S_B(i)$, it suffices to show that $\lim_{\mu(i)\to\infty}[S_A(i)+S_B(i)] \geq 1$. Indeed,

$$\lim_{\mu(i)\to\infty}[S_A(i)+S_B(i)] = 1.$$

Therefore, $S_A(i) + S_B(i) > 1$ for any $\tau > 0$ and any $\mu(i)$.

Finally, we prove the relationships obtained in Proposition 1. First, let us consider the volatility of quasi-difference. Using (A2), we have

$$\Delta_\lambda \hat{q}_t(i) = (S_A(i) + S_B(i) - 1)\frac{(1-\lambda_i)(1-\lambda_i\beta)}{1-\lambda_i\beta\rho}\hat{z}_t(i),$$

where $\Delta_\lambda \hat{q}_t(i) = \hat{q}_t(i) - \lambda_i \hat{q}_{t-1}(i)$. Because $\hat{z}_t(i)$ follows an AR(1) process,

$$\Delta_\lambda \hat{q}_t(i) = \rho\Delta_\lambda \hat{q}_{t-1}(i) + (S_A(i) + S_B(i) - 1)\frac{(1-\lambda_i)(1-\lambda_i\beta)}{1-\lambda_i\beta\rho}\xi_t(i),$$

where $\xi_t(i) = \xi_{A,t}(i) - \xi_{B,t}(i)$. Let $Var(\Delta_\lambda q(i)) = \mathbb{E}[\Delta_\lambda \hat{q}_t(i)]^2$. Since $\xi_t(i)$ and $\Delta_\lambda \hat{q}_{t-1}(i)$ are uncorrelated, $Var(\Delta_\lambda q(i)) = \rho^2 Var(\Delta_\lambda q(i)) + \{(S_A(i)+S_B(i)-1)(1-\lambda_i)(1-\lambda_i\beta)/(1-\lambda_i\beta\rho)\}^2\sigma_\xi^2$, where $\sigma_\xi = \sqrt{\sigma_{\xi_A}^2 + \sigma_{\xi_B}^2}$. Hence,

$$Var(\Delta_\lambda q(i)) = (S_A(i) + S_B(i) - 1)^2\left[\frac{(1-\lambda_i)(1-\lambda_i\beta)}{1-\lambda_i\beta\rho}\right]^2\frac{\sigma_\xi^2}{1-\rho^2},$$

which is decreasing in λ_i and increasing in τ.

Second, we compute $std(q(i))$. From (A2), we obtain

$$\hat{q}_t(i) = (\lambda_i + \rho)\hat{q}_{t-1}(i) - \lambda_i\rho\hat{q}_{t-2}(i) + (S_A(i) + S_B(i) - 1)\frac{(1-\lambda_i)(1-\lambda_i\beta)}{1-\lambda_i\beta\rho}\xi_t(i). \tag{A3}$$

Thus, the stochastic process of $\hat{q}_t(i)$ is an AR(2) process. In a general autocovariance computation for an AR(2) process, the variance of $\hat{q}_t(i)$ satisfies

$$\frac{1+\phi_2}{1-\phi_2}\left[1 - 2\phi_2 + \phi_2^2 - \phi_1^2\right]Var(q(i)) = \psi^2\sigma_\xi^2,$$

where $\phi_1 = \lambda_i + \rho$, $\phi_2 = -\lambda_i\rho$, $\psi = (S_A(i)+S_B(i)-1)(1-\lambda_i)(1-\lambda_i\beta)/(1-\lambda_i\beta\rho)$ and $Var(q(i)) = \mathbb{E}[q(i)]^2$. Substituting these parameters yields

$$\frac{1-\lambda_i\rho}{1+\lambda_i\rho}\left[1 + 2\lambda_i\rho + (\lambda_i\rho)^2 - (\lambda_i + \rho)^2\right]Var(q(i)) = \psi^2\sigma_\xi^2.$$

Thus,

$$\begin{aligned} Var(q(i)) &= (S_A(i) + S_B(i) - 1)^2\frac{1}{(1+\lambda_i\rho)^2 - (\lambda_i+\rho)^2}\frac{1+\lambda_i\rho}{1-\lambda_i\rho}\frac{(1-\lambda_i)^2(1-\lambda_i\beta)^2}{(1-\lambda_i\beta\rho)^2}\sigma_\xi^2 \\ &= (S_A(i) + S_B(i) - 1)^2\left[\frac{1-\lambda_i}{1-\lambda_i\rho}\right]\left[\frac{1+\lambda_i\rho}{1+\lambda_i}\right]\left[\frac{1-\lambda_i\beta}{1-\lambda_i\beta\rho}\right]^2\frac{\sigma_\xi^2}{1-\rho^2}, \end{aligned}$$

which implies that $std(q(i))$ is decreasing in λ_i and increasing in τ.

Finally, we move on to $std(\Delta q(i))$. By taking the difference of (A3), we obtain

$$\begin{aligned}\Delta\hat{q}_t(i) &= (\lambda_i+\rho)\Delta\hat{q}_{t-1}(i) - \lambda_i\rho\Delta\hat{q}_{t-2}(i) \\ &+(S_A(i)+S_B(i)-1)\frac{(1-\lambda_i)(1-\lambda_i\beta)}{1-\lambda_i\beta\rho}(\xi_t(i)-\xi_{t-1}(i)).\end{aligned}$$

Let $\gamma_0 = \mathbb{E}(\Delta\hat{q}_t(i)\Delta\hat{q}_t(i))$, $\gamma_1 = \mathbb{E}(\Delta\hat{q}_t(i)\Delta\hat{q}_{t-1}(i))$, and $\gamma_2 = \mathbb{E}(\Delta\hat{q}_t(i)\Delta\hat{q}_{t-2}(i))$. By simple algebra, we can obtain

$$\begin{aligned}\gamma_0 &= \phi_1\gamma_1 + \phi_2 + [2-\phi_1]\psi^2\sigma_\xi^2 \\ (1-\phi_2)\gamma_1 &= \phi_1\gamma_0 - \psi^2\sigma_\xi^2 \\ \gamma_2 &= \phi_1\gamma_1 + \phi_2\gamma_0.\end{aligned}$$

Eliminating γ_1 and γ_2 yields

$$\gamma_0 = \frac{2\psi^2}{(1+\phi_1-\phi_2)(1+\phi_2)}\sigma_\xi^2 = \frac{2\psi^2}{(1+\lambda_i+\rho+\lambda_i\rho)(1-\lambda_i\rho)}\sigma_\xi^2.$$

In other words, from the definition of ψ

$$Var(\Delta q(i)) = \gamma_0 = \frac{2(S_A(i)+S_B(i)-1)^2}{1+\rho}\left[\frac{1-\lambda_i}{1+\lambda_i}\right]\left[\frac{1-\lambda_i}{1-\lambda_i\rho}\right]\left[\frac{1-\lambda_i\beta}{1-\lambda_i\beta\rho}\right]^2\sigma_\xi^2,$$

which immediately follows that $std(\Delta q(i))$ decreases with λ_i and increases with τ.

References

Baba, C. (2007): "Price Dispersion across and within Countries: The Case of Japan and Korea," *Journal of the Japanese and International Economies*, 21(2), 237–259.

Bergin, P. R., and R. C. Feenstra (2001): "Pricing-to-market, Staggered Contracts, and Real Exchange Rate Persistence," *Journal of International Economics*, 54(2), 333–359.

Bils, M., and P. J. Klenow (2004): "Some Evidence on the Importance of Sticky Prices," *Journal of Political Economy*, 112(5), 947–985.

Broda, C., and D. E. Weinstein (2008): "Understanding International Price Differences Using Barcode Data," NBER Working paper # 14017.

Calvo, G. (1983): "Staggered Prices in a Utility-Maximizing Framework," *Journal of Monetary Economics*, 12(3), 383–398.

Ceglowski, J. (2003): "The Law of One Price: Intranational Evidence for Canada," *Canadian Journal of Economics*, 36(2), 373–400.

Chari, V. V., P. J. Kehoe, and E. R. McGrattan (2002): "Can Sticky Price Models Generate Volatile and Persistent Real Exchange Rates?," *Review of Economics Studies*, 69(3), 533–563.

Cheung, Y.-W., and E. Fujii (2008): "Deviations from the Law of One Price in Japan," CESifo Working paper No 1456.

Choi, C.-Y., and K. Matsubara (2007): "Heterogeneity in the Persistence of Relative Prices: What Do the Japanese Cities Tell Us?," *Journal of the Japanese and International Economies*, 21(2), 260–286.

Crucini, M. J., and M. Shintani (2008): "Persistence in Law of One Price Deviations: Evidence from Micro-data," *Journal of Monetary Economics*, 55(3), 629–644.

Crucini, M. J., M. Shintani, and T. Tsuruga (2008): "Accounting for Persistence and Volatility of Good-level Real Exchange Rates: the Role of Sticky Information," NBER Working Paper # 14381.

Crucini, M. J., C. I. Telmer, and M. Zachariadis (2005): "Understanding European Real Exchange Rates," *American Economic Review*, 95(3), 724–738.

Engel, C., and J. H. Rogers (1996): "How Wide is the Border?," *American Economic Review*, 86(5), 1112–1125.

Goldberg, P. K., and F. Verboven (2004): "Market Integration and Convergence to the Law of One Price: Evidence from the European Car Market," *Journal of International Economics*, 65(1), 49–73.

Higo, M., and Y. Saita (2007): "Price Setting in Japan: Evidence from CPI Micro Data," Bank of Japan Working Paper Series E-20.

Kehoe, P. J., and V. Midrigan (2007): "Sticky Prices and Sectoral Real Exchange Rates," Federal Reserve Bank of Minneapolis Working Paper No 656.

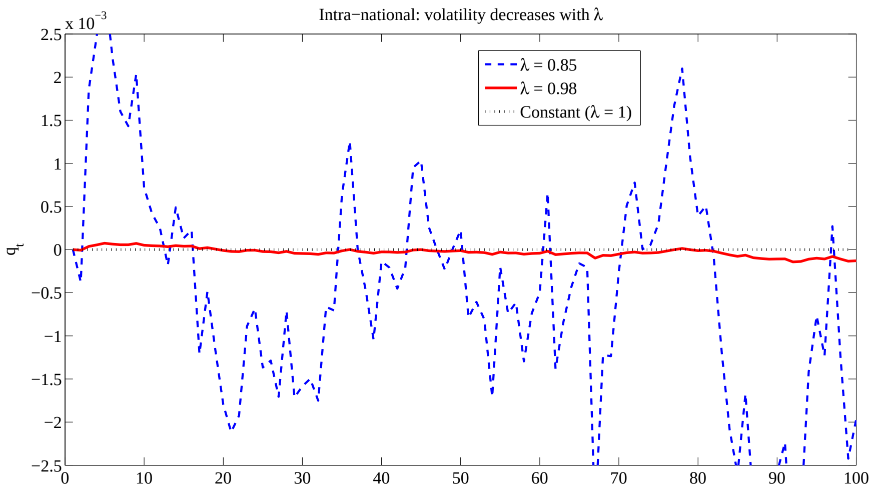
Klenow, P., and O. Kryvtsov (2008): "State-Dependent or Time-Dependent Pricing: Does It Matter for Recent U.S. Inflation?," *Quarterly Journal of Economics*, 123(3), 863–904.

Nakamura, E., and J. Steinsson (2008): "Five Facts About Prices: A Reevaluation of Menu Cost Models," *Quarterly Journal of Economics*, 123(4), 1415–1464.

Parsley, D. C., and S.-J. Wei (1996): "Convergence to the Law of One Price Without Trade Barriers or Currency Fluctuations," *Quarterly Journal of Economics*, 111(4), 1211–1236.

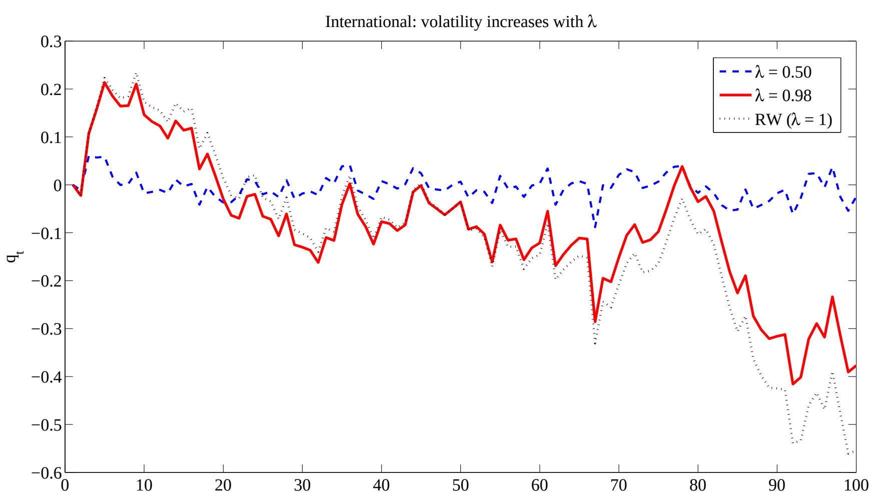
——— (2001): "Explaining the Border Effect: the Role of Exchange Rate Variability, Shipping Costs, and Geography," *Journal of International Economics*, 55(1), 87–105.

Figure 1: Volatility of intra-national LOP deviations and price stickiness



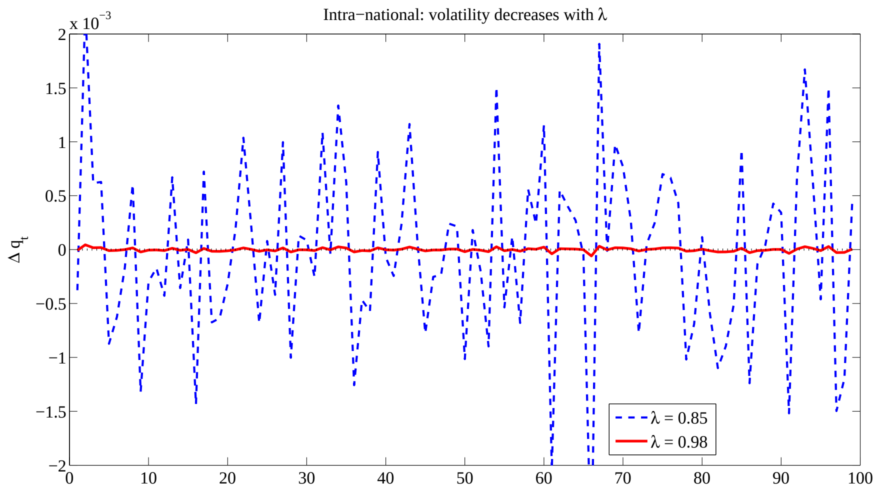
NOTES: Simulated from (23).

Figure 2: Volatility of international LOP deviations and price stickiness



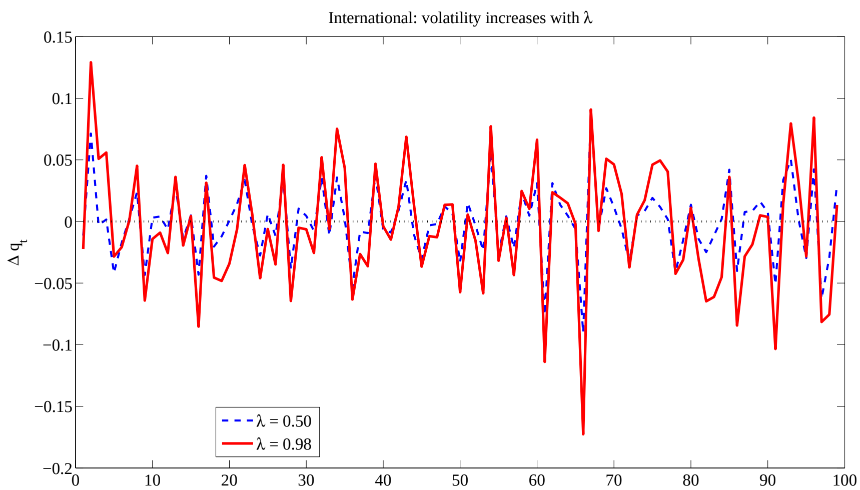
NOTES: Simulated from (24).

Figure 3: Volatility of the first differenced intra-national LOP deviations and price stickiness



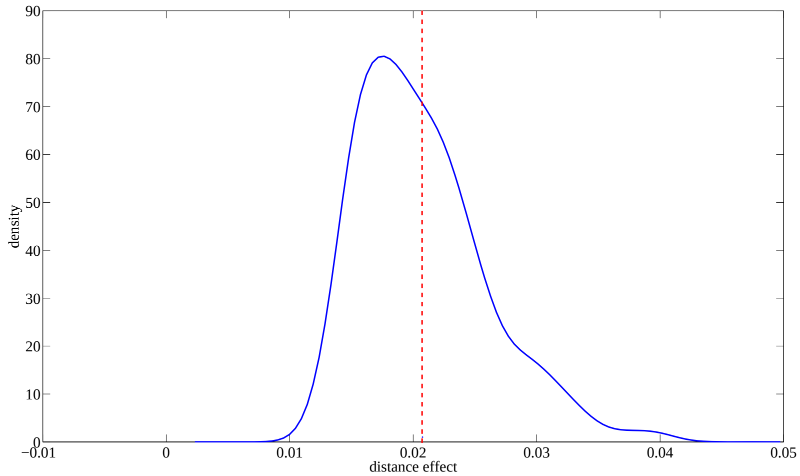
NOTES: Simulated from (23).

Figure 4: Volatility of the first differenced international LOP deviations and price stickiness



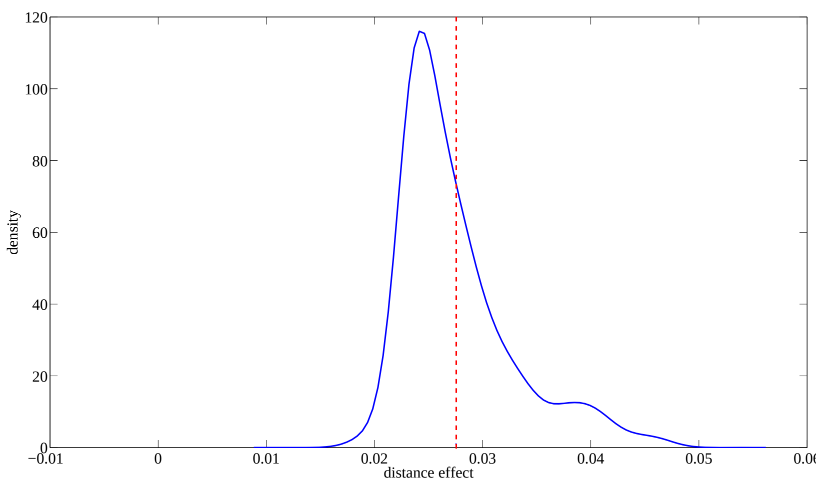
NOTES: Simulated from (24).

Figure 5: Kernel density estimation of the distance effect (standard deviation)



NOTES: The dotted line represents the average effect of 0.021.

Figure 6: Kernel density estimation of the distance effect (inter-quartile range)



NOTES: The dotted line represents the average effect of 0.028.

Table 1: Infrequency of regular price changes and standard deviations of first-differenced LOP deviations by categories of goods

	Category (number of goods)	Obs.	λ_i		$std(\Delta q(i))$
1	Food at home (210)	13052	80.5	[0.28]	6.3
2	Food away from home (24)	1363	97.7	[0.01]	1.6
3	Alcoholic beverages (14)	850	92.5	[0.04]	1.5
4	Shelter (26)	1487	98.0	[0.15]	1.5
5	Fuel and other utilities (33)	2068	97.8	[0.07]	0.9
6	Household furnishings and operations (91)	5077	90.6	[0.13]	5.7
7	Men's and boys' apparel (32)	1934	88.9	[0.10]	5.2
8	Women's and girls' apparel (34)	1808	73.7	[0.17]	4.9
9	Footwear (8)	567	93.7	[0.01]	4.8
10	Transportation (28)	1449	99.2	[0.06]	0.4
11	Medical care (31)	1715	96.8	[0.05]	2.1
12	Personal care (25)	1391	95.9	[0.09]	2.0
13	Entertainment (66)	3423	97.0	[0.11]	2.5
1-13	All goods (622)	36184	91.2	[0.22]	4.3

NOTES: All categories are grouped to make close matches to the ELI code issued by Bureau of Labor Statistics in the US for comparisons. The numbers in parenthesis following the category name shows the number of goods for computation of infrequencies of price changes. The number of observations (Obs.) is the one used for calculating the frequencies and not for calculating standard deviations of LOP deviations. Infrequencies of price changes are the median infrequencies and shown as a percent per month. The numbers in the brackets are standard deviations for the computed infrequencies. The last column shows the median of unconditional standard deviations of the first differenced relative prices used in the regressions described in Table 6. The unit is in percent.

Table 2: Price volatility regressions

Transformation	Standard deviation			Inter-quartile range		
	Log dist.	Infreq.(λ_i)	Adj. R^2	Log dist.	Infreq.(λ_i)	Adj. R^2
Difference	0.035	-0.173	0.51	0.043	-0.249	0.73
	(0.0003)	(0.002)		(0.0003)	(0.002)	
Quasi-difference	0.032	-0.156	0.49	0.043	-0.241	0.70
	(0.0002)	(0.002)		(0.0003)	(0.002)	
None	0.034	-0.132	0.11	0.045	-0.167	0.07
	(0.0003)	(0.002)		(0.0005)	(0.003)	

NOTES: All regressions have 46 city-pair dummies as explanatory variables as well as the variables shown in the table. 'Log dist.', 'Infreq.' and 'Adj. R^2' abbreviate log distance, the infrequency of price changes and adjusted R^2, respectively. Numbers in parenthesis are heteroskedasticity consistent standard errors. The first three columns show regression results when the regressand is the standard deviation. The standard deviations are calculated from the first differenced, the quasi-differenced and the non-filtered relative price. The second three columns show regression results when inter-quartile range is used. To compute time-series variability, we use the sample period from January 2000 to December 2006.

Table 3: Price volatility regressions with good-specific distance effect

Transformation	Standard deviation			Inter-quartile range		
	Log dist.	Infreq.(λ_i)	Adj. R^2	Log dist.	Infreq.(λ_i)	Adj. R^2
Difference	0.021	-0.077	0.74	0.028	-0.138	0.85
	(0.001)	(0.007)		(0.001)	(0.008)	
Quasi-difference	0.019	-0.066	0.72	0.026	-0.123	0.82
	(0.001)	(0.007)		(0.001)	(0.0097)	
None	0.024	-0.060	0.48	0.032	-0.075	0.37
	(0.001)	(0.009)		(0.002)	(0.016)	

NOTES: All regressions have 46 city-pair dummies and good-specific distance effect as explanatory variables as well as the variables shown in the table. See also the footnote of Table 2 for the other detail.

Table 4: Price volatility regressions with city-pair-specific volatility of technological difference

Transformation	Standard deviation				Inter-quartile range			
	Log dist.	Infreq.(λ_i)	Tech. Diff.(σ_j)	Adj. R^2	Log dist.	Infreq.(λ_i)	Tech. Diff. (σ_j)	Adj. R^2
Difference	0.002	-0.173	0.025	0.50	0.001	-0.249	0.020	0.72
	(0.0003)	(0.002)	(0.016)		(0.0003)	(0.002)	(0.014)	
Quasi-difference	0.002	-0.156	0.040	0.48	0.001	-0.241	0.038	0.70
	(0.0003)	(0.002)	(0.015)		(0.0003)	(0.002)	(0.015)	
None	0.005	-0.132	0.100	0.11	0.007	-0.167	0.159	0.07
	(0.0005)	(0.002)	(0.032)		(0.001)	(0.003)	(0.051)	

NOTES: Constant terms are suppressed in all regressions. Regressions include the standard deviation of city-pair-specific volatility of technological difference, denoted by 'Tech. Diff.' as an explanatory variable. See also the footnote of Table 2 for the other detail.

Table 5: Price volatility regressions with city-pair-specific volatility of technological difference and good-specific distance effect

Transformation	Standard deviation				Inter-quartile range			
	Log dist.	Infreq.(λ_i)	Tech. Diff.(σ_j)	Adj. R^2	Log dist.	Infreq.(λ_i)	Tech. Diff.(σ_j)	Adj. R^2
Difference	0.002	-0.077	0.025	0.72	0.001	-0.138	0.020	0.84
	(0.0002)	(0.007)	(0.011)		(0.0002)	(0.008)	(0.010)	
Quasi-difference	0.002	-0.066	0.041	0.71	0.002	-0.123	0.038	0.81
	(0.0002)	(0.007)	(0.011)		(0.0002)	(0.010)	(0.012)	
None	0.005	-0.060	0.106	0.47	0.007	-0.075	0.167	0.36
	(0.0004)	(0.010)	(0.025)		(0.001)	(0.016)	(0.042)	

NOTES: Constant terms and are suppressed in all regressions. Regressions have good-specific distance effects and include the standard deviation of city-pair-specific volatility of technological difference, denoted by 'Tech. Diff.' as an explanatory variable. See also the footnote of Table 2 for the other detail.

Table 6: Price volatility regressions by categories of goods

Category	Standard deviation			Inter-quartile range			Obs.
	Log dist.	Infreq.(λ_i)	Adj. R^2	Log dist.	Infreq.(λ_i)	Adj. R^2	
1	0.034	-0.166	0.55	0.042	-0.234	0.67	7747
	(0.0003)	(0.002)		(0.0003)	(0.002)		
2	0.218	-1.267	0.46	0.008	-0.047	0.04	690
	(0.012)	(0.072)		(0.001)	(0.008)		
3	0.048	-0.276	0.27	0.035	-0.206	0.39	597
	(0.004)	(0.027)		(0.003)	(0.017)		
4	0.011	-0.042	-0.01	0.011	-0.063	0.20	736
	(0.002)	(0.012)		(0.001)	(0.005)		
5	0.014	-0.066	0.11	0.002	-0.014	0.00	552
	(0.003)	(0.016)		(0.0004)	(0.002)		
6	0.031	-0.134	0.21	0.038	-0.215	0.58	2519
	(0.001)	(0.006)		(0.001)	(0.005)		
7	0.122	-0.697	0.65	0.116	-0.688	0.80	574
	(0.004)	(0.027)		(0.003)	(0.021)		
8	0.170	-0.981	0.52	0.071	-0.406	0.08	230
	(0.010)	(0.058)		(0.008)	(0.046)		
9	0.016	-0.040	0.13	0.038	-0.216	0.05	321
	(0.016)	(0.097)		(0.013)	(0.081)		
10	0.012	-0.058	-0.03	0.018	-0.102	0.73	446
	(0.002)	(0.011)		(0.0005)	(0.003)		
11	0.059	-0.326	0.28	0.055	-0.325	0.70	644
	(0.003)	(0.019)		(0.002)	(0.012)		
12	0.066	-0.372	0.67	0.053	-0.312	0.75	1012
	(0.002)	(0.009)		(0.001)	(0.008)		
13	0.029	-0.144	0.17	0.037	-0.218	0.81	1729
	(0.001)	(0.006)		(0.001)	(0.006)		
1-13	0.035	-0.173	0.51	0.043	-0.249	0.73	17797
	(0.0003)	(0.002)		(0.0003)	(0.002)		

NOTES: Numbers in Category column from 1 to 13 correspond to categories in Table 1. 'Obs.' denotes the number of observations. Regressands are volatility measures of the first differenced relative price. See also the footnote of Table 2 for the detail.

Table 7: Price volatility regressions by categories of goods with good-specific distance effect

Category	Standard deviation			Inter-quartile range			Obs.
	Log dist.	Infreq.(λ_i)	Adj. R^2	Log dist.	Infreq.(λ_i)	Adj. R^2	
1	0.018	-0.037	0.73	0.024	-0.081	0.79	7747
	(0.001)	(0.008)		(0.001)	(0.009)		
2	0.327	-1.915	0.58	0.014	-0.080	0.68	690
	(0.065)	(0.383)		(0.008)	(0.047)		
3	0.042	-0.242	0.48	0.042	-0.250	0.51	597
	(0.024)	(0.151)		(0.017)	(0.105)		
4	0.025	-0.132	0.56	0.001	-0.003	0.76	736
	(0.012)	(0.075)		(0.002)	(0.013)		
5	-0.013	0.096	0.41	0.002	-0.009	0.86	552
	(0.009)	(0.053)		(0.001)	(0.004)		
6	0.025	-0.095	0.51	0.028	-0.146	0.77	2519
	(0.004)	(0.027)		(0.003)	(0.022)		
7	0.145	-0.843	0.75	0.131	-0.781	0.86	574
	(0.018)	(0.115)		(0.020)	(0.124)		
8	0.233	-1.363	0.57	0.116	-0.681	0.81	230
	(0.049)	(0.300)		(0.035)	(0.213)		
9	0.101	-0.567	0.25	-0.026	0.186	0.57	321
	(0.092)	(0.569)		(0.052)	(0.322)		
10	-0.009	0.068	0.35	0.016	-0.090	0.94	446
	(0.007)	(0.044)		(0.002)	(0.011)		
11	0.058	-0.320	0.51	0.082	-0.490	0.85	644
	(0.015)	(0.094)		(0.014)	(0.086)		
12	0.061	-0.345	0.81	0.059	-0.349	0.79	1012
	(0.007)	(0.041)		(0.008)	(0.051)		
13	0.008	-0.012	0.51	0.011	-0.056	0.89	1729
	(0.004)	(0.025)		(0.003)	(0.022)		
1-13	0.021	-0.077	0.74	0.028	-0.138	0.85	17797
	(0.001)	(0.007)		(0.001)	(0.008)		

NOTES: See the footnote of Tables 2 and 6 for the detail.