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Noisy information, distance and law of one price dynamics across US cities*

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Abstract

Using micro price data across US cities, we provide evidence that both the volatility and persistence of deviations from the law of one price (LOP) are positively correlated with the distance between cities. A standard, two-city, equilibrium model with time-varying technology under homogeneous information can predict the relationship between the volatility and distance but not between the persistence and distance. To account for the latter fact, we augment the standard model with noisy signals about the state of nominal aggregate demand that are asymmetric across cities. We further establish that the interaction of imperfect information and sticky prices improves the fit of the model.

JEL Classification: E31; F31; D40

Keywords: Real exchange rates, Law of one price, Relative prices, Trade cost

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1 Introduction

Trade costs still matter even among highly integrated economies. Anderson and van Wincoop (2004) show how theoretical gravity models of trade rationalize a negative relationship between bilateral trade flows and distance or a positive relationship between bilateral price deviations and distance. In this context, distance is viewed as a reasonable proxy for trade costs between cities or countries. They show that a variant of a static Ricardian model of Eaton and Kortum (2002) can explain the cross-sectional dispersion of the law of one price (LOP) deviations with trade costs that vary across location pairs. A similar implication can also be obtained using the static gravity model of Helpman, Melitz and Rubinstein (2008) which allows self-selection of firms into export markets.[1] In the macroeconomics literature, time-series volatility of LOP deviations often replaces cross-sectional dispersion when running a gravity-type regression. For example, Engel and Rogers (1996) and Parsley and Wei (2001) find that the higher volatility is associated with greater distance between cities. Crucini, Shintani, and Tsuruga (2010a, hereafter CST) develop a simple dynamic rational expectations model where intra-national LOP deviations are driven by time-varying technology, and claim that it can account for the positive correlation between the time-series volatility and trade costs.

In addition to the volatility, the persistence has long been employed in the macroeconomic literature when evaluating the degree of LOP deviations using time-series data. Compared to the volatility-distance correlation, however, less attention has been paid to the persistence-distance correlation.[2] We aim to fill this gap. The main objective of this paper is to understand both empirically and theoretically whether LOP persistence is rising in the distance separating retail markets. Using micro data on price differences across US cities, we find that persistence, as well as volatility, is positively correlated with the distance between cities. We then provide a theoretical framework to explain this empirical finding. We show that the simple setting of CST, which can explain the positive volatility-distance correlation, does not explain the positive persistence-distance correlation. We thus extend the basic dynamic model of CST to incorporate imperfect common knowledge developed by Woodford (2003), Angeletos and La'O (2009), among others.

In the macroeconomics literature, it has been widely argued that heterogeneous expectations with imperfect common knowledge help to generate more plausible predictions about

[1] See Kano, Kano and Takechi (2010).

[2] Few exceptions include Parsley and Wei (1996), Cecchetti, Mark and Sonara (2004), and Choi and Matsubara (2007).

the inflation-output trade-off than homogeneous expectations. Woodford (2003) extends the model of Lucas (1972) and Phelps (1970) with homogeneous expectations by introducing assumptions of (i) heterogenous expectations with strategic complementarities in firm's decision making under monopolistic competition and (ii) nominal aggregate demand shocks which cannot be commonly known even in the long-run. Subsequent work by Angeletos and La'O (2009) simplifies the second assumption to the case where shocks will be publicly known after one period, and suggest that the introduction of sticky prices into the flexible price model of imperfect common knowledge can improve predictions on inflation and output dynamics (see also Fukunaga, 2007). Following this line of research, we apply information frictions to explain the persistence and volatility of intra-national LOP deviations. In particular, we ask if the model armed with heterogeneous expectations can account for the positive persistent-distance correlation.[3] In answering the question, we modify a dynamic model of intra-national LOP deviations used in CST by introducing the assumption of heterogeneous expectations about the state of nominal demand across cities in the economy. Our analytical result shows that our two-city model can successfully explain both the persistence-distance and the volatility-distance correlations, when information precision across cities is heterogenous. We also confirm that our results are robust to extensions that includes sticky prices or more than two cities.

The intuition is that intra-national LOP deviations with imperfect information consist of two components: technological differences across two locations, and information heterogeneity about nominal shocks across two locations. In our model, the latter is not as persistent as the former, since the difference in perception between locations disappears after one period. Overall persistence of LOP deviations is thus determined by the relative importance of the two components. A positive technology shock in one location generates LOP deviations since price reductions fail to transmit fully to the other location in the presence of trade costs. Therefore, when the trade cost is high, the relative contribution from persistent technological differentials becomes large and LOP deviations become more persistent. This implies a positive correlation between trade costs and persistence of LOP deviations.

Persistence of the real exchange rates have long attracted the economists' attention both at the aggregate level (Frankel, 1986, Rogoff, 1996, and Lothian and Taylor, 1996) and at the disaggregated level (Parsley and Wei, 1996, Crucini and Shintani, 2008) since violation

[3] An alternative approach of introducing heterogeneous expectations is to consider infrequent information updating scheme refered to as sticky information by Mankiw and Reis (2002). Crucini, Shintani, and Tsuruga (2010b) introduce sticky information structure to a multi-city model to increase the predicted persistence of LOP deviations, but not to generate correlation between the persistence and distance.

of mean reversion suggests that purchasing power parity and LOP do not hold even in the long-run. One possible explanation for the high observed persistence of the deviations is the non-linearity of response generated by the presence of trade costs. For example, Obstfeld and Taylor (1997) estimate a threshold autoregressive (TAR) model with the price differential following a random walk within the band of arbitrage but converging to the level of trade cost from outside the band.[4] Taylor (2001) points out that when the threshold (which may be interpreted as a measure of trade cost) becomes larger, observed persistence becomes higher. Anderson and van Wincoop (2004), however, express some reservations and argue that such an arbitrage equation is "of limited relevance in understanding the link between price differentials and trade costs in most markets (p. 738)."

Below, we begin with our empirical evidence in Section 2. In Section 3, we provide a theoretical model and investigate its implications for LOP dynamics. Robustness of the our result to some extensions is discussed in Section 4. Section 5 concludes.

2 Regressions

2.1 Data

We use quarterly data on the individual prices from the *American Chamber of Commerce Researchers Association* (ACCRA) *Cost of Living Index* produced by the Council of Community and Economic Research. The original ACCRA *Cost of Living Index* includes 75 goods and services across 632 cities. However, to construct the balanced panel, the numbers of goods and services and cities were reduced to 48 items and 52 cities, respectively. The sample period is from 1990:Q1 to 2007:Q4. The data is the same as used by Yazgan and Yilmazkuday (2011).[5]

In measuring the LOP deviations, we follow Crucini and Shintani (2008) and consider all possible city pairs for each good or service. Let $q_{j,k,t}(i)$ be the LOP deviation measured as the log of the price of good i in city j relative to the price of the same good in city k:

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

for $i = 1, 2, ..., 48$ and for any $j \neq k$. Here j and k $(= 1, 2, ..., 52)$ index the cities. Because

[4] See also Michael, Nobay, and Peel (1996) and O'Connell (1998).

[5] For the detailed explanation on the selection of goods and services and cities, see Yazgan and Yilmazkuday (2011).

the number of cities is 52, the total number of city pairs is 1,326 in our data set. We follow Parsley and Wei (1996) and divide goods and services into three categories: tradable perishables, tradable non-perishables and non-tradable services. With this categorization, we have 14 perishables, 18 non-perishables, and 16 services.[6]

For each of 63,648 ($48 \times 1,326$) series of relative prices, we first compute volatility and persistence measures. For volatility, we compute the standard deviations of $q_{j,k,t}(i)$ and $\Delta q_{j,k,t}(i) = q_{j,k,t}(i) - q_{j,k,t-1}(i)$ over time, which are reported in the first two upper panels of Table 1. The volatility measures of each series are very close to the results of Parsley and Wei (1996) who use the ACCRA *Cost of Living Index* over 1975:Q1 - 1992:Q4 and report that the average standard deviation ranges from 12.9 to 14.9 percent. Turning to persistence, we employ two measures, ρ^{OLS} and ρ^{MU}, each of which is obtained by estimating an AR(1) model of $q_{j,k,t}(i)$ for each good and city pair separately (running 63,648 autoregressions in total), using the ordinary least squares and the median unbiased estimator, respectively. The two lower panels of Table 1 report the summary statistics of persistence measures across all series. The averages over all goods and services are 0.52 for ρ^{OLS} and 0.55 for ρ^{MU}. These values are consistent with the literature based on micro price data in that the half-lives are much shorter in the disaggregated series than the aggregate series.[7]

2.2 Regression results

Our regressions evaluate the effect of trade cost on volatility and persistence of LOP deviations. The literature has found that the volatility of the relative prices of the same goods sold between two different cities is positively associated with a proxy for the trade cost. The trade cost is approximated by the log of the greater circle distance between two cities j and k.[8] The main difference between our analysis and the existing literature is that we also apply

[6]In particular, each category includes the following goods and services: Perishables are steak, ground beef, frying chicken, milk, eggs, margarine, cheese, potatoes, bananas, lettuce, bread, hamburger, pizza, and fried chicken; non-perishables are chunk light tuna, coffee, sugar, corn flakes, canned peas, canned peaches, facial tissues, washing powder, shortening, frozen corn, soft drink, gasoline, toothpaste, shampoo, men's shirt, tennis balls, beer, and wine; and services are monthly rent for apartment, total home purchase price, mortgage rate, monthly payment for house, total energy cost, telephone, auto maintenance, doctor, dentist, man's haircut, beauty salon, dry cleaning, appliance repair, newspaper subscription, a first-run movie ticket, and bowling.

[7]Regarding the half-life of the disaggregated relative prices for US cities, Parsley and Wei (1996) estimate half-life to be from 4 to 15 quarters. Crucini and Shintani (2008) report 18 months and Yazgan and Yilmazkuday (2011) find half-lives ranging from 1.1 to 2.8 quarters. Our estimates of persistence are somewhat low, compared to Yazgan and Yilmazkuday (2011). The difference may arise because we use the AR(1) model to measure the persistence while Yazgan and Yilmazkuday (2011) use the sum of AR coefficients.

[8]This approach of using the log of the greater circle distance to impose the concavity between the variability and the distance was taken by Engel and Rogers (1996), Parsley and Wei (1996, 2001) and others.

the distance regression to the persistence measure of the LOP deviations.

Table 2 reports the traditional volatility-distance regression results for a variety of specifications. When all goods are pooled (with good dummies), the volatility measures have significantly positive correlations with the log-distance, based on heteroskedasticity consistent standard errors reported below the estimates. The magnitudes of coefficients are broadly in line with the previous studies such as Parsley and Wei (1996) for the dependent variable of $std\,(q)$ and Engel and Rogers (1996) for the dependent variable of $std\,(\Delta q)$.

For robustness, we also run regressions with the degree of price stickiness replacing good-specific dummy variables. This specification is in the spirit of Crucini, Shintani, and Tsuruga (2010a) who discuss the effect of price stickiness on the variability of the LOP deviations. Here, the degree of price stickiness is the probability of no price changes at a quarterly frequency measured by $(1-f_i)^3$, where f_i is the monthly frequency of price changes calculated from Nakamura and Steinsson (2008).[9] Although the regression fit substantially decreases in terms of the adjusted R-squared when good dummies are replaced by a single regressor of the degree of price stickiness, the coefficient on the log-distance is essentially unaltered from the case with good dummies. Furthermore, the coefficients on the degree of price stickiness (not reported in the table) are highly comparable, in both sign and magnitude, to CST who use the Japanese micro price data and to Hickey and Jacks (2011) who use Canadian micro price data.[10]

While the existing literature assigns an important role for trade costs in the determination of LOP volatility, relatively little attention has been paid to the relationship between trade costs and LOP persistence. Table 3 shows results of persistence regressions where we regress ρ^{OLS} and ρ^{MU} on the same independent variables as the volatility regression in Table 2. The table suggests a significant positive correlation between the persistence of the LOP deviations and log-distance when we pool all goods in the regression. Again, all regressions include good dummies except for regressions with price stickiness which use estimates of price stickiness instead of good dummies.[11] On average, a one percent increase in distance between cities

[9] Nakamura and Steinsson (2008) calculate the frequency of price changes for over 300 items in the US using the underlying micro price data collected by the Bureau of Labor Statistics to construct the Consumer Price Index (CPI) over 1998 - 2005. For regressions, we matched the Entry Level Items in the CPI with items in the ACCRA *Cost of Living Index*.

[10] In particular, the estimates are -0.032 with the standard errors of 0.001 for the dependent variable of $std(q)$ and -0.061 with the standard errors of 0.001 for the dependent variable of $std\,(\Delta q)$. Our results remain robust to the use of the different measures of frequency of price changes by Bils and Klenow (2004) and Klenow and Kryvtsov (2008).

[11] As discussed in Kehoe and Midrigan (2007), Carvalho and Nechio (2011), and Crucini, Shintani, and Tsuruga (2010b), the higher degree of price stickiness tends to give rise to higher persistence of the LOP

leads to an increment of persistence by 0.02. When we split the categories of goods into perishables, non-perishables, and services, we see significant positive correlations particularly for tradable perishable and non-perishable goods.

Our findings on the relationship between persistence and distance are broadly consistent with the few previous works on the topic. For example, Parsley and Wei (1996) report positive coefficients on the interaction terms of lagged relative prices and the (log) distance in augmented Dickey-Fuller regressions of relative prices between pairs of US cities. Their results imply that the convergence rate, measured by the sum of AR coefficients, is slower between cities of greater spatial separation. Cecchetti, Mark, and Sonara (2002) examine the persistence of deviations from purchasing power parity (rather than LOP) using historical aggregate price indexes of 19 US cities from 1918 to 1995, and find that both the sum of AR coefficients and half-lives are positively correlated with (log) distance. Choi and Matsubara (2007) investigate sector-level price data from Japanese cities and find that, for 22 out of 36 items, the estimated half-lives are positively correlated with (log) distance after controlling for the population differences between cities. Although estimation results from previous works described above may not be directly comparable to ours due to differing data and methods, the positive relationship between persistence and distance has been gaining empirical support in the literature.

2.3 Theoretical prediction from the CST model

A natural question to ask is whether empirically tractable models of the intra-national LOP deviations are consistent with the observed positive correlation between both LOP volatility and persistence and distance. Our starting point is the two-city model developed by CST. In their model, firms in a city have a city-specific labor productivity and the difference in the log labor productivity $z_t(i)$ drive the short-run fluctuations of the inter-city LOP deviations $q_t(i)$. With the assumption that $z_t(i)$ follows a stationary AR(1) process with AR coefficient $\rho_z(i)$ and that the firm cannot change the prices with a probability $\lambda(i)$, one can express dynamics of $q_t(i)$ by

$$q_t(i) = \lambda(i) q_{t-1}(i) + \frac{[(1-\lambda(i)]\,[1-\lambda(i)\beta]}{1-\lambda(i)\beta\rho_z(i)}(2s-1)z_t(i), \qquad (1)$$

deviations. Indeed, the coefficients for the degree of price stickiness are 0.209 when ρ^{OLS} is used and 0.216 when ρ^{MU} is used for the dependent variables, respectively.

where $s = 1/\left[1 + (1+\tau)^{1-\xi}\right] > 1/2$ is the "home bias" parameter and is an increasing function of trade cost τ and the elasticity of substitution across varieties ξ, and β is the discount factor satisfying $0 < \beta < 1$. This home bias parameter can be interpreted as the steady state expenditure share on home-made goods.

In equation (1), volatility increases with trade cost because a rise in τ increases $2s-1$ and thus amplifies the fluctuation of $z_t(i)$ via $2s-1$. In contrast, the persistence of the LOP deviations is invariant to the trade cost τ. For example, when $\rho_z(i) = 0$, $z_t(i)$ becomes an i.i.d. random variable, and the persistence of $q_t(i)$ corresponds to $\lambda(i)$. If $\rho_z(i) \neq 0$ and $\lambda(i) = 0$, the persistence of $q_t(i)$ is simply $\rho_z(i)$. Finally, if $\rho_z(i) \neq 0$ and $\lambda(i) \neq 0$, the persistence is given by $[\lambda(i) + \rho_z(i)]/[1 + \lambda(i)\rho_z(i)]$ which does not depend on s.

Crucini, Shintani, and Tsuruga (2010b) introduce sticky information about monetary shocks into an international model of LOP deviations based on price stickiness in an attempt to explain the relationship between the persistence and volatility of international LOP deviations with the observed degrees of price stickiness. We could extend the CST's intra-national model of the LOP deviation by assuming this type of imperfect information on both monetary shocks and shocks to labor productivity. Suppose that firms cannot update their information set with a probability ω. The probability here is common across firms in the economy. By extending the CST model with sticky information, we can show that $q_t(i)$ follows the second-order difference equation:

$$q_t(i) = [\lambda(i) + \omega\rho_z(i)]\, q_{t-1}(i) - \lambda(i)\,\omega\rho_z(i)\, q_{t-2}(i) + \frac{(1-\omega)\,[(1-\lambda(i)]\,[[1-\lambda(i)\beta]}{(1-\lambda(i)\beta\rho_z(i))}(2s-1) z_t(i)\,. \tag{2}$$

This equation generalizes (1) but, once again, it can be shown that the persistence of $q_t(i)$ is independent of trade cost τ under the extended model. Though the sticky information could increases the persistence with a larger ω, the increase occurs, irrespective of trade cost τ. In other words, it does not seem fruitful to focus on price stickiness or information frictions to account for the correlation between distance and persistence, at least as these features have been incorporated into recent models of the LOP.

In the next section, we show that heterogeneous imperfect information can explain the relationship between the persistence and trade cost.

3 Model

3.1 Two-city model

The economy consists of two cities 1 and 2, both of which are located within the same country. The economy is populated by a single representative household and a continuum of firms. Trade is over a continuum of goods between the two cities. Under monopolistic competition, firms set prices to satisfy demand for a particular good in a particular city (i.e., pricing to market). The representative household chooses consumption and labor supply over an infinite horizon subject to a cash-in-advance (CIA) constraint. In what follows, the unit of time is one quarter.

We consider three levels of constant-elasticity-of-substitution (CES) aggregation. The lowest level of aggregation is across brands v. Here, brands produced in city 1 are indexed $v \in [0,1]$ while those produced in city 2 are indexed $v \in (1,2]$. Integrating over brands of a particular good i sold in a particular city $j(=1,2)$ gives the CES index $C_{j,t}(i) = \left[(1/2)^{1/\xi}\int_0^2 C_{j,t}(i,v)^{(\xi-1)/\xi}dv\right]^{\xi/(\xi-1)}$, where $\xi > 1$. Here $C_{j,t}(i)$ denotes the consumption of good i consumed in city j and $C_{j,t}(i,v)$ denotes consumption of brand v of good i sold in city j. The middle level of aggregation across consumption in the two cities for good $i \in [0,1]$ is given by $C_t(i) = \left[(1/2)^{1/\xi}\sum_{j=1}^2 C_{j,t}(i)^{(\xi-1)/\xi}\right]^{\xi/(\xi-1)}$ and the highest level of aggregation is national consumption $C_t = \left[\int_0^1 C_t(i)^{(\xi-1)/\xi}di\right]^{\xi/(\xi-1)}$. Similarly, the corresponding CES price indexes at the lowest, middle, and highest levels are respectively defined as $P_{j,t}(i) = \left[(1/2)\int_0^2 P_{j,t}(i,v)^{1-\xi}dv\right]^{1/(1-\xi)}$, $P_t(i) = \left[(1/2)\sum_{j=1}^2 P_{j,t}(i)^{1-\xi}\right]^{1/(1-\xi)}$, and $P_t = \left[\int_0^1 P_t(i)^{1-\xi}di\right]^{1/(1-\xi)}$.

Households in this economy trade complete state-contingent money claims and choose consumption (C_t) and labor supply (L_t) over an infinite horizon subject to budget and cash-in-advance (CIA) constraints. When household instantaneous utility is given by $\ln C_t - \chi L_t$, the intra-temporal first-order condition between consumption and labor becomes $W_t/P_t = \chi C_t$ where W_t is the nominal wage rate. By substituting the CIA constraint $\Theta_t = P_t C_t$ into the condition, the nominal wage rate is proportional to the nominal money demand (or equivalently the aggregate nominal expenditure): $W_t = \chi\Theta_t$. In this paper, we assume that the log of aggregate nominal expenditure ($\theta_t = \ln\Theta_t$) follows a random walk process:

$$\theta_t = \theta_{t-1} + \varepsilon_t^\theta, \qquad \varepsilon_t^\theta \sim N(0,\sigma_\theta^2). \tag{3}$$

The firms' technology is:

$$Y_t(i,v) = Z_t(i,v) \left[\Gamma_t^d(i,v)\right]^{\alpha} \left[L_t^d(i,v)\right]^{1-\alpha}, \tag{4}$$

where $Y_t(i,v)$, $Z_t(i,v)$, $\Gamma_t^d(i,v)$, and $L_t^d(i,v)$ denote output, exogenous productivity, and the input of composite intermediate goods, and labor input, respectively. Here $\alpha \in [0,1)$ is the share of intermediate goods representing the degree of strategic complementarities (see Huang, Liu, and Phaneuf, 2004).

Note that the intermediate goods purchased by each firm are a composite of all goods. Therefore, the market clearing condition for intermediate goods is given by $\int_0^1 \int_0^2 \Gamma_t^d(i,v)\,dvdi = \Gamma_t$ where Γ_t is aggregate intermediate goods defined similarly to C_t with the brand-level intermediate goods sold in city j, $\Gamma_{j,t}(i,v)$. In addition, we assume that firms must pay the iceberg transportation cost $\tau(>0)$ to carry their goods between cities. Thus, the market clearing conditions for each brand of each good satisfy

$$Y_t(i,v) = \left[C_{1,t}(i,v) + \Gamma_{1,t}(i,v)\right] + (1+\tau)\left[C_{2,t}(i,v) + \Gamma_{2,t}(i,v)\right] \quad \text{for } v \in [0,1] \tag{5}$$

$$Y_t(i,v) = (1+\tau)\left[C_{1,t}(i,v) + \Gamma_{1,t}(i,v)\right] + \left[C_{2,t}(i,v) + \Gamma_{2,t}(i,v)\right] \quad \text{for } v \in (1,2]. \tag{6}$$

The market clearing condition for labor is given by $\int_0^1 \int_0^2 L_t^d(i,v)\,dvdi = L_t$.

We assume that productivity $(z_t(i,v) = \ln Z_t(i,v))$ is common across brands but specific to the good and the place of production:

$$z_t(i,v) = \begin{cases} z_{1,t}(i) & \text{for } v \in [0,1] \\ z_{2,t}(i) & \text{for } v \in (1,2] \end{cases} \tag{7}$$

Furthermore, as a source of persistence, log-productivity in city ℓ, namely $z_{\ell,t}(i)$, follows a stationary AR(1) process

$$z_{\ell,t}(i) = \rho_z(i) z_{\ell,t-1}(i) + \varepsilon_{\ell,t}^z(i), \qquad \varepsilon_{\ell,t}^z(i) \sim N(0, \sigma_z^2(\ell)) \tag{8}$$

with $0 < \rho_z(i) < 1$. Note that AR coefficients can vary across goods so that variance of $z_{\ell,t}(i)$ is good-dependent. We further assume that $\sigma_z^2(\ell)$ is location specific such that the productivity innovations for good i are drawn from a distribution with dispersion that is location specific. This allows for the possibility that variation of technology shocks may differ across the place of production so that variance of $z_{\ell,t}(i)$ is not only good-dependent but also is location dependent.[12]

3.2 Information structure

Following Angeletos and La'O (2009), we assume that each period is divided in two stages: In stage 1, prices are set under imperfect information; In stage 2, the information on θ_t is revealed, and consumption and employment choices are made taking the prices predetermined in stage 1 as given. Building on the framework of Angeletos and La'O (2009), we introduce retail managers who decide prices for each firm. Managers set prices for the firm's brands in the city in which they live. The retail managers are assumed to be fully informed about the productivity of their own firm, but imperfectly informed about the current state of nominal aggregate demand.

In particular, in stage 1, retail managers receive idiosyncratic noisy signals $x_{j,t}(i,v)$ of θ_t:

$$x_{j,t}(i,v) = \theta_t + \varepsilon^x_{j,t}(i,v), \quad \text{where } \varepsilon^x_{j,t}(i,v) \sim N\left(0, \sigma^2_x(j)\right). \tag{9}$$

We allow retail managers' signals and variability of noise $\varepsilon^x_{j,t}(i,v)$ to differ across cities j. As in the case of $\varepsilon^z_{\ell,t}(i)$, we assume that the variability $\sigma^2_x(j)$ is location specific such that shocks to signals $\varepsilon^x_{j,t}(i)$ are drawn from a distribution with dispersion that is location specific. This reflects the assumption that retail managers are isolated in city j in terms of their information and receive idiosyncratic signals of the nominal aggregate demand with different levels of precision.

In stage 2, the level of aggregate nominal expenditure becomes common knowledge. Let $\mathbb{I}_{j,t}(i,v)$ and $\mathbb{I}'_{j,t}(i,v)$ be the information sets in period t, for the retail managers in city j at stages 1 and 2, respectively. Within period t, the retail managers' information set evolves as follows:

$$\begin{aligned} \mathbb{I}_{j,t}(i,v) &= \mathbb{I}'_{j,t-1}(i,v) \cup [x_{j,t}(i,v), z_t(i,v)] \\ \mathbb{I}'_{j,t}(i,v) &= \mathbb{I}_{j,t}(i,v) \cup \{\theta_t\}. \end{aligned} \tag{10}$$

Note that the information is purely idiosyncratic: Since the information differs across j (i.e., where retail managers live) and brand v, the information set must specify the index j and v.

In the baseline model, we assume flexible prices for all goods to focus attention on the

[12] For simplicity, the aggregate component of $z_{\ell,t}(i)$ is assumed to be a constant (i.e., $\int z_{\ell,t}(i)\,di$ is a constant.)

role of trade costs and information frictions. The log linearization of the optimal individual prices, with suppressed constant terms, yields,

$$p_{j,t}(i,v) = (1-\alpha)\,\mathbb{E}_{j,t}(\theta_t|i,v) + \alpha\mathbb{E}_{j,t}(p_t|i,v) - z_t(i,v)\,, \tag{11}$$

where $p_{j,t}(i,v) = \ln P_{j,t}(i,v)$, $p_t = \ln P_t$, and $\mathbb{E}_{j,t}(\cdot|i,v)$ denotes the expectations operator conditional on $\mathbb{I}_{j,t}(i,v)$. Note that θ_t appears in the pricing equation because the nominal wage rate in our model is proportional to the aggregate nominal expenditure.[13]

The log price index for good i sold in city 1 can be approximated by

$$p_{1,t}(i) = s\int_0^1 p_{1,t}(i,v)\,dv + (1-s)\int_1^2 p_{1,t}(i,v)\,dv. \tag{12}$$

The price of the same good sold in city 2, $p_{2,t}(i)$, is similarly derived. Recall that the expenditure share s represents the degree of expenditure bias toward home-made goods. According to (12), this home bias makes the home city price index more sensitive to a price of home-produced goods than that of goods produced in the other city. Since a larger home bias is caused by more costly transportation of goods, s is increasing in τ.

3.3 Results

We now investigate equilibrium dynamics of the LOP deviations, focusing on implications of noisy information. In what follows, we define the LOP deviations between two cities as $q_t(i) = \ln[P_{2,t}(i)/P_{1,t}(i)]$. To solve the model with noisy information, we utilize the method of undetermined coefficients to find the solution for $q_t(i)$. We leave the detailed derivation for Appendix A.1 and focus on key equations in what follows.

We use a standard signal extraction problem to specify the expectations on θ_t:

$$\mathbb{E}_{j,t}(\theta_t|i,v) = \kappa_j x_{j,t}(i,v) + (1-\kappa_j)\,\theta_{t-1} \quad \text{for } j = 1,2, \tag{13}$$

where κ_j is the steady state Kalman gain defined as $[1/\sigma_x^2(j)]\,/\,\{[1/\sigma_x^2(j)] + (1/\sigma_\theta^2)\}$. Note that a larger κ_j implies more precise signals because it corresponds to a smaller $\sigma_x^2(j)$. We make the following guess for the form of the aggregate price index: $p_t = c_0\theta_t + c_1\theta_{t-1}$, where c_0

[13] In general, the optimal prices differ across the location of sales because of the presence of the trade cost. However, since we suppressed the constant term which depends on the trade cost, (11) can be used for both cases of $j = \ell$ and $j \neq \ell$.

and c_1 are undetermined coefficients. Given the guess for p_t, combining (12) and (13) yields

$$p_{1,t}(i) = (1-\alpha+\alpha c_0)\kappa_1 \varepsilon_t^\theta + (1-\alpha+\alpha c_0+\alpha c_1)\theta_{t-1} - s z_{1,t}(i) - (1-s) z_{2,t}(i), \quad (14)$$

where we use the fact that the integration over the individual signals washes out idiosyncratic noise $\varepsilon_{j,t}^x(i,v)$. The relative price $q_t(i) = p_{2,t}(i) - p_{1,t}(i)$ is then given by

$$q_t(i) = \phi\varepsilon_t^\theta + (2s-1)z_t(i), \quad (15)$$

where $z_t(i) = z_{1,t}(i) - z_{2,t}(i)$, $\phi = [(1-\alpha)\hat{\kappa}]/(1-\alpha\bar{\kappa})$, $\bar{\kappa} = (\kappa_1+\kappa_2)/2$ and $\hat{\kappa} = \kappa_2 - \kappa_1$.

As shown in (15), LOP deviations are driven by two components, an i.i.d. shock to the aggregate nominal expenditure ε_t^θ and the technological differentials between two cities $z_t(i)$. To see the intuition why ε_t^θ matters for $q_t(i)$, note that randomly drawn variance of noise $\sigma_x^2(j)$ in each city j leads to different precision of signals of the nominal demand shocks across cities. Individual prices could respond to signals more strongly in a city with more precise signals than in the other city. This difference in responses of prices to the aggregate nominal expenditure between cities gives rise to a deviation of price indexes across the two cities in the impact period. However, this information differential only lasts for one period because ε_t^θ is assumed to be common knowledge in the next period. Thus, the prices revert to their steady state values and the LOP deviation caused by the informational differential disappears in the next period.

In (15), the LOP deviations are also driven by $z_t(i)$. Here $z_t(i)$ represents the technological difference between two cities and its coefficient $(2s-1)$ is increasing in the degree of home bias s. To understand how $z_t(i)$ affects LOP deviations, suppose that the place-of-production-specific shock $z_{1,t}(i)$ increases by one percent. The technological improvement in city 1 decreases the price index in city 1 by larger amount than the price index in city 2 due to home bias in the price index (i.e., $s > 1/2$). Thus $q_t(i)$ remains above the steady state value until $z_{1,t}(i)$ converges to its steady state level.

From (15), the standard deviations and the first-order autocorrelation of $q_t(i)$ are respectively given by

$$std[q_t(i)] = \sqrt{\phi^2\sigma_\theta^2 + (2s-1)^2 var[z_t(i)]}, \quad (16)$$

and

$$\rho_q(i) = \frac{(2s-1)^2 var[z_t(i)]}{\phi^2\sigma_\theta^2 + (2s-1)^2 var[z_t(i)]}\rho_z(i). \quad (17)$$

The following proposition summarizes properties on the short-run dynamics of the LOP deviations.

Proposition 1 *Under the preference assumption of* $\ln C - \chi L$*, the CIA constraint, the assumption on the stochastic processes of aggregate nominal expenditure (3) and productivity (8), and the pricing assumption with imperfect information specified as (9) and (10), LOP deviations have the following properties:*

(i) Volatility: $std\left[q_t(i)\right]$ *increases with trade cost* τ*:*

$$\frac{\partial std\left[q_t(i)\right]}{\partial \tau} > 0.$$

(ii)Persistence:

1. *When information on* θ_t *is perfect (i.e.,* $\sigma_x(1) \to 0$ *and* $\sigma_x(2) \to 0$*),* $\rho_q(i)$ *is independent of trade cost* τ*:*
$$\frac{\partial \rho_q(i)}{\partial \tau} = 0.$$
2. *When information on* θ_t *is imperfect and managers in different cities have asymmetric information precision about the state of aggregate nominal demand (i.e.,* $\hat{\kappa} \neq 0$*),* $\rho_q(i)$ *increases with trade cost* τ*:*
$$\frac{\partial \rho_q(i)}{\partial \tau} > 0.$$

The proposition implies that, assuming that distance between two locations is a proxy for trade cost τ, the model with perfect information can account for the observed positive volatility-distance correlation but fails to predict the observed positive persistence-distance correlation. In contrast, the imperfect information can account for both observations.

To see the intuition for property (i), again suppose there is a one percent increase in the productivity of city 1. If trade cost is absent, the steady state expenditure share s equals 1/2, which implies that price indexes in both cities fall by the same amount and the relative price, $q_t(i) = p_{2,t}(i) - p_{1,t}(i)$, remains unchanged. In contrast, the presence of the trade cost causes home bias and price index in city 1 falls more than that in city 2. Higher trade costs amplify this expenditure asymmetry which causes higher volatility of relative prices.

As shown above, the model cannot account for a positive correlation between persistence and trade cost under perfect information. In this case, an increase in θ_t leads to an increase in the price index in both cities but the effect of a change in θ_t on the price indexes cancels out because managers increase prices by the same amount in the two cities. As a result, the relative prices are solely determined by the technological differences and the persistence of $q_t(i)$ corresponds to the persistence of $z_t(i)$ which is independent of the trade cost.

The final property in Proposition 1 can be explained as follows: When heterogeneous imperfect information is present, (15) shows that the persistence of $q_t(i)$ are determined by the persistence of ε_t^θ and $z_t(i)$. The relative volatility of aggregate nominal demand and productivity shocks matters for the persistence of the LOP deviations because the persistence of ε_t^θ is zero while that of $z_t(i)$ is $\rho_z(i) > 0$. Now, suppose that the trade cost is completely absent. Under no home bias ($2s - 1 = 0$), technological differentials do not affect LOP deviations. Instead, the i.i.d. shock ε_t^θ drives LOP deviations and thus, the LOP deviation follows an i.i.d. process. However, if a trade cost is present, technological differentials contribute to fluctuations of $q_t(i)$ and increase the persistence of $q_t(i)$ via the persistence of $z_t(i)$. As a result, the persistence of LOP deviations becomes larger as trade cost becomes higher because technological differentials have a larger weight in generating persistence.[14]

The results here do not hold when $z_{\ell,t}(i)$ is independent of the place of production ℓ. However, Appendix A.2 shows that, if the model has city-specific preference shocks biased toward home-made goods and if the preference shocks in the two cities are persistent, the same qualitative results are obtained. Thus, our results do not critically depend on the presence of technology shocks specific to the place of production.

3.4 Numerical examples

To see the effect of noisy information from various sources, we conduct some sensitivity analysis on the relationship of volatility and persistence with trade cost by changing parameters in ϕ. In the benchmark calibration, we set parameters so that the persistence and standard deviations implied from the model roughly match those from the data in Table 1, which reports that ρ_q and $std[q(i)]$ are, on average, 0.52 and 14 percent respectively. In particular, for the source of the relative price fluctuations, we set ρ_z at 0.55, the average of $\sigma_z(\ell)$ at 0.20 and σ_θ at 0.10.[15] For the city-specific degrees of imperfect information which determines κ_j, the signal-to-noise ratios are $\sigma_x^2(1)/\sigma_\theta^2 = 3$ and $\sigma_x^2(2)/\sigma_\theta^2 = 1/3$, leading to $\kappa_1 = 0.75$ and

[14] Indeed, the relative importance of technological difference on the persistence of LOP can be measured by the coefficient of $\rho_z(i)$ in (17).

[15] To match the volatility of the LOP deviations from the model with the data, we set σ_θ at 10 percent, which is large compared with the data where the standard deviation of nominal GDP over the 1990:Q1 - 2007:Q1 period is only 0.5 percent. However, under the model with price stickiness in Section 4.2, σ_θ is reduced to a level comparable with the data.

$\kappa_2 = 0.25$. These calibrations imply that $\bar{\kappa} = 0.50$ and $\hat{\kappa} = 0.50$. We set $\alpha = 0.90$ and $\xi = 4$, consistent with the literature.[16] Finally, we allow the trade cost to vary in the range $(0, 0.50]$.

Figure 1 reconfirms the properties obtained in Proposition 1. The right panel of the figure shows that, regardless of values of information differentials, the volatility of LOP deviations depends positively on τ. In contrast, the figure also shows that the curves for the persistence in the left panel are upward-sloping only when $\hat{\kappa}$ is non-zero. If $\hat{\kappa} = 0$ as in the case of perfect information, the curve for the persistence is flat at $\rho_z(i) = 0.55$.

The figure also compares the impact of $\hat{\kappa}$ on persistence and volatility by changing $\hat{\kappa}$ from 0.25 to 1.0 while holding $\bar{\kappa}$ at 0.50. This increase in $\hat{\kappa}$ can be interpreted as a larger information differential between cities, and thus ϕ, ceteris paribus, increases. The increase in ϕ leads to a decline in the persistence of the LOP deviation because a larger information differential increases the weight of the i.i.d. nominal demand shock relative to the weight of the persistent productivity shock in the determination of the LOP deviation. A larger information differential generates higher volatility via a larger ϕ, but, under our parameterization, the quantitative impact is small.

Figure 2 shows the impact of $\bar{\kappa}$ on persistence and volatility by changing $\bar{\kappa}$ from 0.25 to 0.75 while holding $\hat{\kappa} = 0.5$. A low value of $\bar{\kappa}$ corresponds to the lower degree of information precision for the economy as a whole, because $\bar{\kappa}$ is the average of the Kalman gains that are positively related to precision of signals received in the two cities. When signals of θ_t are noisier, retail managers' pricing becomes less sensitive to changes in the aggregate nominal demand and ϕ declines. Hence, the LOP deviations are more persistent (See the left panel of Figure 2). Once again, however, the right panel shows shifts of the curve for volatility appears to be virtually unaffected.

Finally, Figure 3 conducts a sensitivity analysis regarding strategic complementarities. In Woodford's (2003) model of monetary non-neutrality where prices fluctuate according to shocks to aggregate nominal expenditure, he has emphasized that strategic complementarities can generate substantial persistence in output dynamics. In our model of LOP deviations, strategic complementarities also affect both the persistence and volatility of relative prices. Stronger strategic complementarities raise the persistence because price indexes are more persistent, through smaller ϕ. However, smaller ϕ also dampens the volatility, since the effect of ε_t^θ on the relative price is weakened by a smaller ϕ. Thus, there is a tradeoff between matching the persistence and volatility of LOP deviations when using the strategic

[16] See Angeletos and La'O (2009) and Mankiw and Reis (2002) for α. We follow Broda and Weinstein (2006) to calibrate ξ.

complementarity parameter.

4 Extensions

4.1 Introducing price stickiness

The baseline model assumes that prices of all goods are completely flexible for simplicity. Empirical studies on micro price data, however, have discovered substantial heterogeneity in the degree of price stickiness across goods. The empirical results in Section 2 also controlled for price stickiness instead of using good dummies and found that trade cost remains positively correlated with volatility and persistence. This subsection introduces price stickiness into the baseline model to see whether our analytical results are robust to the extension. To this end, we follow Kehoe and Midrigan (2007) and CST who assume Calvo-type price stickiness where the degree of price stickiness differs across goods but is common across locations. Each period, retail managers can reset their price with a constant probability $1 - \lambda(i)$. In what follows, we set the degree of strategic complementarities α at zero because it allows us to analytically derive the effect of sticky prices.

Appendix A.3 shows that the log-approximated reset price $p^*_{j,t}(i,v)$, with suppressed constant terms, takes the following form:

$$p^*_{j,t}(i,v) = [1 - \lambda(i)\beta] \sum_{h=0}^{\infty} [\lambda(i)\beta]^h \mathbb{E}_{j,t}[\theta_{t+h} - z_{t+h}(i,v)|i,v]. \tag{18}$$

This optimal reset price equals the weighted average of the expected current and all future marginal costs due to the non-zero probability of being unable to change prices. Likewise, Calvo-type price stickiness changes the evolution of the log-price index in city 1 to

$$p_{1,t}(i) = \lambda(i) p_{1,t-1}(i) + [1 - \lambda(i)] \left[s \int_0^1 p^*_{1,t}(i,v)\, dv + (1-s) \int_1^2 p^*_{1,t}(i,v)\, dv \right]. \tag{19}$$

The log-price index in city 2 is similarly derived. Appendix A.3 also shows that the LOP deviations are given by the first-order difference equation:

$$q_t(i) = \lambda(i) q_{t-1}(i) + [1 - \lambda(i)] \left[\hat{\kappa}\varepsilon^\theta_t + \frac{1 - \lambda(i)\beta}{1 - \lambda(i)\beta\rho_z(i)} (2s-1) z_t(i) \right]. \tag{20}$$

As discussed in Kehoe and Midrigan (2007), the Calvo-type price stickiness raises the persistence of the LOP deviations.[17] In this first-order difference equation, shocks to $q_t(i)$ are $\hat{\kappa}\varepsilon_t^\theta + [1-\lambda(i)\beta] / [1-\lambda(i)\beta\rho](2s-1)z_t(i)$. This term has interpretations similar to (15). Indeed, this expression consists of a temporary nominal shock and a persistent technological differential. The coefficient for ε_t^θ is $\hat{\kappa}$, which corresponds to ϕ in (15) when $\alpha = 0$. The coefficient on $z_t(i)$ is $[1-\lambda(i)\beta] / [1-\lambda(i)\beta\rho_z(i)](2s-1)$ which is again increasing in trade cost. The new multiplier $[1-\lambda(i)\beta] / [1-\lambda(i)\beta\rho_z(i)]$ (≤ 1) reflects that sticky prices make retail managers respond less to shocks to technology compared to the case of flexible prices. Because the expression inside the brackets in (20) takes a similar form to (15), the properties in Proposition 1 can be applied to this expression and the same intuition continues to hold. In other words, the higher trade cost still gives rise to more volatile and persistent $q_t(i)$ through larger home bias, though the quantitative implications are different.

Using the model with price stickiness, we again investigate whether the model can explain the observed empirical regularities by calibration. In addition to the parameterization $\alpha = 0$ for simplicity, we set parameters in the model to match the persistence and volatility from the data. In the numerical example for the flexible price model, we set σ_θ to 0.10, substantially larger than the data. In the case of the sticky price model, the value of σ_θ is now parameterized to a value much closer to the data: $\sigma_\theta = 0.01$. We set $\rho_z(i)$ at a low value 0.30 in comparison with the previous case since sticky prices generate persistence of $q_t(i)$ and thus there is less need for persistence in the real shocks. We set $\lambda(i)$ at 0.30, which implies prices remain fixed for 4.3 months, consistent with Bils and Klenow (2004).[18] Other parameters continue to be the same as the case of flexible prices: $\sigma_z(\ell) = 0.20$ on average, and $\xi = 4$.

Figure 4 shows that the persistence increases with trade cost only in the case of non-zero information differentials and the volatility is positively correlated with trade cost regardless of the information differentials. However, persistence is now very insensitive to changes in trade cost. With price stickiness, persistence of $q_t(i)$ is determined by persistence both from

[17] In the international setting, Kehoe and Midrigan (2007) argue that persistence and volatility of the LOP deviations should increase with $\lambda(i)$. In particular, their equation for the LOP deviations is given by

$$q_t(i) = \lambda(i)\, q_{t-1}(i) + \lambda(i)\, \Delta S_t,$$

where ΔS_t denotes the nominal exchange rate growth. However, they focus on the relationship between the degree of price stickiness and the persistence (as well as the volatility), instead of the relationship between trade costs and the persistence.

[18] The value of $\lambda(i)$ used here implies somewhat shorter duration of price changes than the median duration of regular price changes reported by other micro price studies using US data. In particular, the reported months are 6.9 months by Klenow and Kryvtsov (2008) and 11.1 month by Nakamura and Steinsson (2008). When we use these values for simulation, the persistence implied from the model is larger than the persistence in the data. Though this gap appears to be interesting anomaly, we leave it for future research.

price stickiness and from technological difference. Since only the latter depends on trade cost, it weakens sensitivity of $q_t(i)$ to τ. Thus, persistence increases only by small amount relative to the previous calibration.

4.2 Multi-city model

The baseline model also assumes only two cities in the economy. A realistic and straightforward exercise may be to increase the number of cities in the model shown in the previous subsection and to explore the implications of multi-city setting for the relationships of trade cost with persistence and volatility. Under this assumption, we note that the price index in city 1 can be expressed as

$$P_{1,t}(i) = \left[\frac{1}{N}\int_0^N P_{1,t}(i,v)^{1-\xi}\,dv\right]^{\frac{1}{1-\xi}}. \tag{21}$$

The equation (19) is generalized to

$$p_{1,t}(i) = \lambda(i)\,p_{1,t-1}(i) + [1-\lambda(i)]\left[s\int_0^1 p^*_{1,t}(i,v)\,dv + (1-s)\frac{1}{N-1}\int_1^N p^*_{1,t}(i,v)\,dv\right], \tag{22}$$

where we suppress constant terms and the home bias parameter is now given by

$$s = \frac{1}{1+(N-1)(1+\tau)^{1-\xi}}.$$

The equation of the log optimal price (18) remains unchanged. Equation (22) tells us that the price index in a city is affected by prices of goods produced in all cities in the economy. The expenditure share s declines as the number of cities increases. Let $q_{j,k,t}(i) = p_{j,t}(i) - p_{k,t}(i)$ be the LOP deviations between city j and k. By taking a simplifying assumption that trade costs are common across cities, it can be shown that

$$q_{j,k,t}(i) = \lambda(i)\,q_{j,k,t-1}(i) + [1-\lambda(i)]\left[\hat{\kappa}_{j,k}\varepsilon^\theta_t + \frac{1-\lambda(i)\beta}{1-\lambda(i)\beta\rho_z(i)}\left(s+\frac{s-1}{N-1}\right)z_{k,j,t}(i)\right], \tag{23}$$

where $z_{k,j,t}(i) = z_{k,t}(i,k) - z_{j,t}(i)$ and $\hat{\kappa}_{j,k} = \kappa_j - \kappa_k$.

Compared to (20) in the case of only two cities, whereas the coefficient for ε^θ_t remains unchanged, that for technological difference is affected by the number of cities. In particular, the former depends on the information differential between two cities $\hat{\kappa}_{j,k}$ and independent of N but, in contrast, the latter declines as N increases. In fact, the expenditure share on home-made goods declines and the fluctuations in technological differential is more weakly transmitted to the LOP deviations.

Nevertheless, the underlying structure of the LOP deviations shown in (23) is similar in structure to that under two-city model. The LOP deviations still include both temporary and persistent components and the coefficient on the technological differential $z_{k,j,t}(i)$ remains an increasing function of τ. This assures that an increase in trade cost generates a stronger home bias, giving rise to a larger contribution of technological differentials to fluctuations of the LOP deviations. Figure 5 presents the persistence and volatility of $q_{j,k,t}(i)$ under $N = 2, 3$, and 5. While the persistence of LOP deviations is less sensitive to changes in trade cost for a larger N, the curve for persistence is still upward-sloping over various τ. The volatility decreases for small N, but continues to show a positive correlation between the volatility and trade cost. Therefore, higher trade cost implies more persistent and more volatile relative prices under the multi-city model with imperfect information.

5 Conclusion

This paper investigates micro data on individual good price differences across US cities to provide empirical evidence that persistence, as well as volatility, of intra-national LOP deviations are positively correlated with the distance between cities. To explain the empirical findings, we develop a simple model of time-varying technology combined with imperfect information about nominal demand shocks. Assuming that distance between two locations is a proxy for trade cost, we found that the model with perfect information can account for the observed positive volatility-distance correlation but fails to predict the observed positive persistence-distance correlation. In contrast, imperfect information about aggregate nominal demand can account for both observations. The key mechanism of imperfect information is that shocks arising from imperfect information are temporary while shocks from technology which are amplified by trade cost are long-lived. When the trade costs are low, the effect of the temporary nominal shock is strong relative to the effect of persistent real shocks on the persistence of LOP deviations. When the trade costs are high, the former is weak relative to the latter and the persistence of LOP deviations approaches the persistence of technology shocks. Without the imperfect information, this change in relative contribution between nominal and real shocks does not arise because nominal shocks do not contribute to persistence in LOP deviations. Our findings suggest the importance of imperfect information for better understanding persistent and volatile LOP deviations.

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A Appendix

A.1 Derivation of (15)

Our guess for the aggregate price index is given by

$$p_t = c_0\theta_t + c_1\theta_{t-1}. \tag{24}$$

This conjecture can be supported by the facts that retail managers who make their forecast of θ_t use the Kalman filter to express the forecast as a function of θ_{t-1} and their own signal $x_{j,t}(i,v)$ of which the cross-sectional average equals θ_t. Furthermore, the aggregate prices are independent on the good-specific technology shock $z_{\ell,t}(i)$, because the cross-sectional average of $z_{\ell,t}(i)$ across goods are assumed to be a constant. In this conjecture, we suppress a constant term since we focus on LOP persistence and volatility.

Under the conjecture, the optimal price of brand v of good i consumed in city j can be written as

$$p_{j,t}(i,v) = (1-\alpha)\mathbb{E}_{j,t}(\theta_t|i,v) + \alpha c_0 \mathbb{E}_{j,t}(\theta_t|i,v) + \alpha c_1\theta_{t-1} - z_t(i,v), \tag{25}$$

from (11). Combining (12), (13) and (25) for $j=1$ yields

$$\begin{aligned} p_{1,t}(i) &= s(1-\alpha+\alpha c_0)\kappa_1\int_0^1 x_{1,t}(i,v)\,dv + (1-s)(1-\alpha+\alpha c_0)\kappa_1\int_1^2 x_{1,t}(i,v)\,dv \\ &\quad + [(1-\alpha+\alpha c_0)(1-\kappa_1)+\alpha c_1]\theta_{t-1} - sz_{1,t}(i) - (1-s)z_{2,t}(i) \\ &= (1-\alpha+\alpha c_0)\kappa_1\theta_t + [(1-\alpha+\alpha c_0)(1-\kappa_1)+\alpha c_1]\theta_{t-1} - sz_{1,t}(i) - (1-s)z_{2,t}(i) \\ &= (1-\alpha+\alpha c_0)\kappa_1\varepsilon_t^\theta + (1-\alpha+\alpha c_0+\alpha c_1)\theta_{t-1} - sz_{1,t}(i) - (1-s)z_{2,t}(i), \end{aligned} \tag{26}$$

where we use the fact that $\int_0^1 x_{1,t}(i,v)\,dv = \int_1^2 x_{1,t}(i,v)\,dv = \theta_t$ and $\varepsilon_t^\theta = \theta_t - \theta_{t-1}$ from (3). This equation corresponds to (14) in the main text. Similarly, we can obtain $p_{2,t}(i)$:

$$p_{2,t}(i) = (1-\alpha+\alpha c_0)\kappa_2\varepsilon_t^\theta + (1-\alpha+\alpha c_0+\alpha c_1)\theta_{t-1} - sz_{2,t}(i) - (1-s)z_{1,t}(i). \tag{27}$$

By taking the relative price, we have

$$q_t(i) = (1-\alpha+\alpha c_0)\hat{\kappa}\varepsilon_t^\theta + (2s-1)z_t(i). \tag{28}$$

The remaining task is to solve for c_0 in (28). To find c_0, we take the log-linearization of $P_t(i) = \left[(1/2)\sum_{j=1}^{2} P_{j,t}(i)^{1-\xi}\right]^{1/(1-\xi)}$. The average of $p_{j,t}(i)$ across two cities is

$$p_t(i) = (1-\alpha+\alpha c_0)\,\bar{\kappa}\theta_t + [(1-\alpha+\alpha c_0)(1-\bar{\kappa}) + \alpha c_1]\,\theta_{t-1} - \frac{1}{2}\sum_{\ell=1}^{2} z_{\ell,t}(i).$$

Taking the integral of this equation across goods (with suppressed constant terms) yields

$$p_t = (1-\alpha+\alpha c_0)\,\bar{\kappa}\theta_t + [(1-\alpha+\alpha c_0)(1-\bar{\kappa}) + \alpha c_1]\,\theta_{t-1},$$

since $\int_0^1 z_{1,t}(i)\,di$ and $\int_1^2 z_{2,t}(i)\,di$ are constant. Matching coefficients on θ_t in the above equation gives

$$c_0 = \frac{(1-\alpha)\,\bar{\kappa}}{1-\alpha\bar{\kappa}} \tag{29}$$

Finally, arranging terms in the coefficient on ε_t^{θ} in (28) yields (15).

A.2 Replacing technology shock with preference shock

In this appendix, we shut down fluctuations of $z_{\ell,t}(i)$ but introduce the preference shock in the price index for $p_{j,t}(i)$. Suppose that the price index in city 1 is given by $P_{1,t}(i) = \left[\Upsilon_{1,t}\int_0^1 P_{1,t}(i,v)^{1-\xi}dv + (1-\Upsilon_{1,t})\int_1^2 P_{1,t}(i,v)^{1-\xi}dv\right]^{1/(1-\xi)}$, where $\Upsilon_{1,t}$ denotes the time-varying preference parameter toward goods produced in city 1 and $P_{2,t}(i)$ is analogously defined. The definition of $C_{j,t}(i)$ and $\Gamma_{j,t}(i)$ also changes, similarly to $P_{j,t}(i)$. Likewise, suppose that the preference shock is given by $\Upsilon_{j,t} = \Upsilon\exp(u_{j,t})$ where $u_{j,t}$ follows an AR(1) process:

$$u_{j,t}(i) = \rho_u u_{j,t-1}(i) + \varepsilon_{u,t}(i).$$

The log price index for good i sold in city 1 is given by

$$p_{1,t}(i) = s\int_0^1 p_{1,t}(i,v)\,dv + (1-s)\int_1^2 p_{1,t}(i,v)\,dv - \frac{s-\Upsilon}{(1-\Upsilon)(\xi-1)}u_{1,t}(i), \tag{30}$$

where $s = \Upsilon/\left[\Upsilon + (1-\Upsilon)(1+\tau)^{1-\xi}\right]$. Here, trade costs lead to a nonzero coefficient on $u_{j,t}(i)$. Under $z_{\ell,t}(i) = 0$ for all t, the optimal price set by retail managers are

$$p_{j,t}(i,v) = (1-\alpha)\,\mathbb{E}_{j,t}(\theta_t|i,v) + \alpha\mathbb{E}_{j,t}(p_t|i,v). \tag{31}$$

Combining (30) and (31) yields

$$\begin{aligned} p_{j,t}(i) &= s(1-\alpha)\int_0^1 \mathbb{E}_{j,t}(\theta_t|i,v)\,dv + (1-s)(1-\alpha)\int_1^2 \mathbb{E}_{j,t}(\theta_t|i,v)\,dv \\ &\quad + s\alpha\int_0^1 \mathbb{E}_{j,t}(p_t|i,v)\,dv + (1-s)\alpha\int_1^2 \mathbb{E}_{j,t}(p_t|i,v)\,dv - \frac{s-\Upsilon}{(1-\Upsilon)(\xi-1)}u_{j,t}(i). \end{aligned}$$

Using the method of undetermined coefficients, we note that the price index for good i should have a solution similar to (28):

$$p_{j,t}(i) = (1-\alpha+\alpha c_0)\kappa_j\varepsilon_t^\theta + (1-\alpha+\alpha c_0+\alpha c_1)\theta_{t-1} - \frac{s-\Upsilon}{(1-\Upsilon)(\xi-1)}u_{j,t}(i),$$

Taking the difference of the price indexes for good i between two cities, we have the LOP deviations:

$$q_t(i) = (1-\alpha+\alpha c_0)\hat{\kappa}\varepsilon_t^\theta - \frac{s-\Upsilon}{(1-\Upsilon)(\xi-1)}u_t(i),$$

where $u_t(i) = u_{1,t}(i) - u_{2,t}(i)$. The coefficient of ε_t^θ in the above equation has the same structure as that in (28). Hence, from (29), we obtain

$$q_t(i) = \phi\varepsilon_t^\theta + \frac{s-\Upsilon}{(1-\Upsilon)(\xi-1)}u_t(i). \tag{32}$$

Note that the coefficient of $u_t(i)$ is increasing in τ, since s is positively correlated with τ. Therefore, with preference shocks, we can obtain the same qualitative results as Proposition 1 even if technology shocks specific to the place of production are not introduced in the model.

A.3 Introducing price stickiness

Under Calvo pricing, retail managers in city j choose the reset price to maximize the expected discounted sum of profits from each market. The demand for their brand is given by $(1/2)\left[P_{j,t}(i,v)/P_{j,t+h}(i)\right]^{-\xi} C_{j,t+h}(i)$. Under $\alpha = 0$, the reset price of goods consumed in city j and sold in the same city solves

$$\max_{P_{j,t}(i,v)} \mathbb{E}_{j,t}\left\{ \sum_{h=0}^{\infty} [\lambda(i)\beta]^h \left(\frac{C_{t+h}}{C_t}\right)^{-1} \left[P_{j,t}(i,v) - \frac{\chi\Theta_{t+h}}{Z_{t+h}(i,v)}\right] \frac{1}{2}\left[\frac{P_{j,t}(i,v)}{P_{j,t+h}(i)}\right]^{-\xi} C_{j,t+h}(i) \middle| i,v \right\}.$$

Here we used the first order conditions for labor supply and money demand to replace W_t with $\chi\Theta_t$. The reset price of goods consumed in city j but sold in a different city solves

$$\begin{aligned}&\max_{P_{j,t}(i,v)} \mathbb{E}_{j,t}\left\{\sum_{h=0}^{\infty}\left[\lambda(i)\beta\right]^h\left(\frac{C_{t+h}}{C_t}\right)^{-1}\left[P_{j,t}(i,v)-(1+\tau)\frac{\chi\Theta_{t+h}}{Z_{t+h}(i,v)}\right]\right.\\&\left.\times\frac{1}{2}\left[\frac{P_{j,t}(i,v)}{P_{j,t+h}(i)}\right]^{-\xi}C_{j,t+h}(i)\right|i,v\Bigg\}.\end{aligned}$$

Without loss of generality, we can consider retail managers who set prices for firms producing in city 1. Let $P^*_{1,t}(i,v)$ and $P^*_{2,t}(i,v)$ be the optimal reset price to solve the maximization problems to sell their goods in cities 1 and 2, respectively. The first order condition for $P^*_{1,t}(i,v)$ and $P^*_{2,t}(i,v)$ are

$$\begin{aligned}0&=\mathbb{E}_{1,t}\left\{\sum_{h=0}^{\infty}\left[\lambda(i)\beta\right]^h\left(\frac{C_{t+h}}{C_t}\right)^{-1}\left[P^*_{1,t}(i,v)-\frac{\xi}{\xi-1}\frac{\chi\Theta_{t+h}}{Z_{t+h}(i,v)}\right]\left[\frac{P^*_{1,t}(i,v)}{P_{1,t+h}(i)}\right]^{-\xi}C_{1,t+h}(i)\right|i,v\right\}\\0&=\mathbb{E}_{2,t}\left\{\sum_{h=0}^{\infty}\left[\lambda(i)\beta\right]^h\left(\frac{C_{t+h}}{C_t}\right)^{-1}\left[P^*_{2,t}(i,v)-(1+\tau)\frac{\xi}{\xi-1}\frac{\chi\Theta_{t+h}}{Z_{t+h}(i,v)}\right]\left[\frac{P^*_{2,t}(i,v)}{P_{2,t+h}(i)}\right]^{-\xi}C_{2,t+h}(i)\right|i,v\right\},\end{aligned}$$

for firms located in city 1. (i.e., $v\in[0,1]$.) In terms of the log optimal reset prices,

$$p^*_{j,t}(i,v)=\left[1-\lambda(i)\beta\right]\sum_{h=0}^{\infty}\left[\lambda(i)\beta\right]^h\mathbb{E}_{1,t}\left[\theta_{t+h}-z_{t+h}(i,v)\,|i,v\right],$$

for $j=1,2$. As discussed in the footnote 13, trade costs do not affect the log-linearized optimal prices when the constant term arising from linearization is suppressed. Given the stochastic process of aggregate nominal expenditure and technology, the equation reduces to

$$p^*_{j,t}(i,v)=\mathbb{E}_{j,t}\left[\theta_t|i,v\right]-\frac{1-\lambda(i)\beta}{1-\lambda(i)\beta\rho_z(i)}z_t(i,v).$$

We next consider the log price index for good i sold in city 1. Due to random sampling of firms under Calvo pricing, the price index for good i in city 1 is

$$P_{1,t}(i)=\left[\lambda(i)P_{1,t-1}(i)^{1-\xi}+\left[1-\lambda(i)\right]\left(\frac{1}{2}\right)\int_0^2 P^*_{1,t}(i,v)^{1-\xi}dv\right]^{\frac{1}{1-\xi}}.$$

The log-linear approximation yields

$$p_{1,t}(i) = \lambda(i) p_{1,t-1}(i) + [1-\lambda(i)] p^*_{1,t}(i), \tag{33}$$

and $p^*_{1,t}(i)$ is given by

$$p^*_{1,t}(i) = s\int_0^1 p^*_{1,t}(i,v)\,dv + (1-s)\int_1^2 p^*_{1,t}(i,v)\,dv.$$

In the above equation, we can interprete $p^*_{1,t}(i)$ as the weighted average of reset prices for goods sold in city 1. This weighted average can be rewritten as

$$\begin{aligned} p^*_{1,t}(i) &= s\left[\int_0^1 \mathbb{E}_{1,t}(\theta_t|i,v)\,dv - \frac{1-\lambda(i)\beta}{1-\lambda(i)\beta\rho_z(i)} z_{1,t}(i)\right] \\ &\quad -(1-s)\left[\int_1^2 \mathbb{E}_{1,t}(\theta_t|i,v)\,dv - \frac{1-\lambda(i)\beta}{1-\lambda(i)\beta\rho_z(i)} z_{2,t}(i)\right]. \end{aligned}$$

and $p^*_{2,t}(i)$ can be analogously derived. Let $q^*_t(i) = p^*_{2,t}(i) - p^*_{1,t}(i)$. Then, the relative reset price is

$$\begin{aligned} q^*_t(i) &= \left\{(1-s)\int_0^1 \mathbb{E}_{2,t}[\theta_t|i,v]\,dv + s\int_1^2 \mathbb{E}_{2,t}[\theta_t|i,v]\,dv\right\} \\ &\quad -\left\{s\int_0^1 \mathbb{E}_{1,t}[\theta_t|i,v]\,dv + (1-s)\int_1^2 \mathbb{E}_{1,t}[\theta_t|i,v]\,dv\right\} \\ &\quad +\frac{1-\lambda(i)\beta}{1-\lambda(i)\beta\rho_z(i)}(2s-1)[z_{1,t}(i) - z_{2,t}(i)]. \end{aligned}$$

Using the steady state Kalman filter, we have

$$\begin{aligned} q^*_t(i) &= \kappa_2\left[(1-s)\int_0^1 x_{2,t}(i,v)\,dv + s\int_1^2 x_{2,t}(i,v)\,dv\right] + (1-\kappa_2)[(1-s)\theta_{t-1} + s\theta_{t-1}] \\ &\quad -\kappa_1\left[s\int_0^1 x_{1,t}(i,v)\,dv + (1-s)\int_1^2 x_{1,t}(i,v)\,dv\right] - (1-\kappa_1)[(1-s)\theta_{t-1} + s\theta_{t-1}] \\ &\quad +\frac{1-\lambda(i)\beta}{1-\lambda(i)\beta\rho_z(i)}(2s-1)[z_{1,t}(i) - z_{2,t}(i)] \\ &= (\kappa_2-\kappa_1)(\theta_t - \theta_{t-1}) + \frac{1-\lambda(i)\beta}{1-\lambda(i)\beta\rho_z(i)}(2s-1)[z_{1,t}(i) - z_{2,t}(i)] \\ &= \hat{\kappa}\varepsilon^\theta_t + \frac{1-\lambda(i)\beta}{1-\lambda(i)\beta\rho_z(i)}(2s-1) z_t(i), \end{aligned} \tag{34}$$

where the second equality comes from the fact that $\int_0^1 x_{j,t}(i,v)\,dv = \int_1^2 x_{j,t}(i,v)\,dv = \theta_t$ and the third equality is from (3). By combining the definition of the LOP deviations, (33), and (34), we can obtain (20).

Table 1: Summary statistics

	Avg.	Std.	Obs.
$std(q)$			
All	0.136	0.038	63,648
Perishables	0.154	0.042	18,564
Non-perishables	0.133	0.030	23,868
Services	0.124	0.039	21,216
$std(\Delta q)$			
All	0.127	0.049	63,648
Perishables	0.163	0.055	18,564
Non-perishables	0.129	0.033	23,868
Services	0.093	0.036	21,216
ρ^{OLS}			
All	0.520	0.151	63,648
Perishables	0.417	0.115	18,564
Non-perishables	0.481	0.096	23,868
Services	0.654	0.136	21,216
ρ^{MU}			
All	0.552	0.156	63,648
Perishables	0.445	0.119	18,564
Non-perishables	0.512	0.100	23,868
Services	0.692	0.141	21,216

NOTES: Each number in the table refers to the basic cross-sectional statistics of time-series properties of $q_{j,k,t}(i)$. The sample period is over 1990:Q1 - 2007:Q4. The LOP deviations are calculated from the log of the relative price of a good or service in a city to the same good or service in a different city. In the first two panels, $std(q)$ is the standard deviation over time of $q_{j,k,t}(i)$ for all possible city pairs and $std(\Delta q)$ is the standard deviation over time for the first difference in $q_{j,k,t}(i)$. The persistence is measured by ρ^{OLS} and ρ^{MU} shown in the third and fourth panels. We estimate ρ^{OLS} and ρ^{MU} from AR(1) estimates by good-by-good ordinary least squares and median unbiased estimator, respectively. In each column, 'Avg.' and 'Std.' denote the average and standard deviations across goods. The 'Obs.' denotes the number of observations.

Table 2: Volatility-distance regressions

Dependent var.	Goods	Log-distance	$\bar{R}^2$
$std(q)$	All	0.008	0.45
		(0.0002)	
	All (with price stickiness)	0.008	0.03
		(0.0003)	
	Category-by-category		
	(i) Perishables	0.010	0.57
		(0.0004)	
	(ii) Non-perishables	0.007	0.48
		(0.0003)	
	(iii) Services	0.008	0.31
		(0.001)	
$std(\Delta q)$	All	0.005	0.52
		(0.0003)	
	All (with price stickiness)	0.005	0.05
		(0.0004)	
	Category-by-category		
	(i) Perishables	0.005	0.65
		(0.0004)	
	(ii) Non-perishables	0.003	0.60
		(0.0002)	
	(iii) Services	0.006	0.21
		(0.001)	

NOTES: The estimation is based on cross-sectional regressions of the LOP variability on the log-distance with good dummies or the degree of price stickiness. The number in each row in the third column is the coefficient on the log-distance and the numbers in parentheses are heteroskedasticity consistent standard errors. The $\bar{R}^2$ in the last column is the adjusted R-squared. The upper panel shows the regression results when the standard deviation of $q_{j,k,t}(i)$ is used for the dependent variable and the lower panel shows the regression results when the standard deviation of the first-differenced $q_{j,k,t}(i)$ is used for the dependent variable. The number of observations in regressions are 18,564 for perishable, 23,868 for non-perishables, 21,216 for services, 63,648 for all items, and 58,344 for the estimation with price stickiness because there are no data of price stickiness for four items related to shelters (i.e., monthly rent for apartment, total home purchase price, mortgage rate, and monthly payment for house).

Table 3: Persistence-distance regressions

Dependent var.	Goods	Log-distance	R^2
ρ^{OLS}	All	0.020	0.40
		(0.001)	
	All (with price stickiness)	0.019	0.05
		(0.001)	
	Category-by-category		
	(i) Perishables	0.030	0.26
		(0.002)	
	(ii) Non-perishables	0.029	0.22
		(0.002)	
	(iii) Services	0.002	0.34
		(0.002)	
ρ^{MU}	All	0.021	0.42
		(0.001)	
	All (with price stickiness)	0.020	0.10
		(0.001)	
	Category-by-category		
	(i) Perishables	0.031	0.26
		(0.002)	
	(ii) Non-perishables	0.030	0.22
		(0.002)	
	(iii) Services	0.002	0.34
		(0.002)	

NOTES: The estimation is based on cross-sectional regressions of the LOP persistence on the log-distance with good dummies or the degree of price stickiness. The upper panel shows the regression results when the OLS estimate of AR(1) regression for $q_{j,k,t}(i)$ is used for the dependent variable and the lower panel shows the regression results when the median unbiased estimate is used for the dependent variable. See also the notes of Table 2 for remaining details.

Figure 1: Effect of information differential $\hat{\kappa}$ on persistence and volatility of LOP deviations

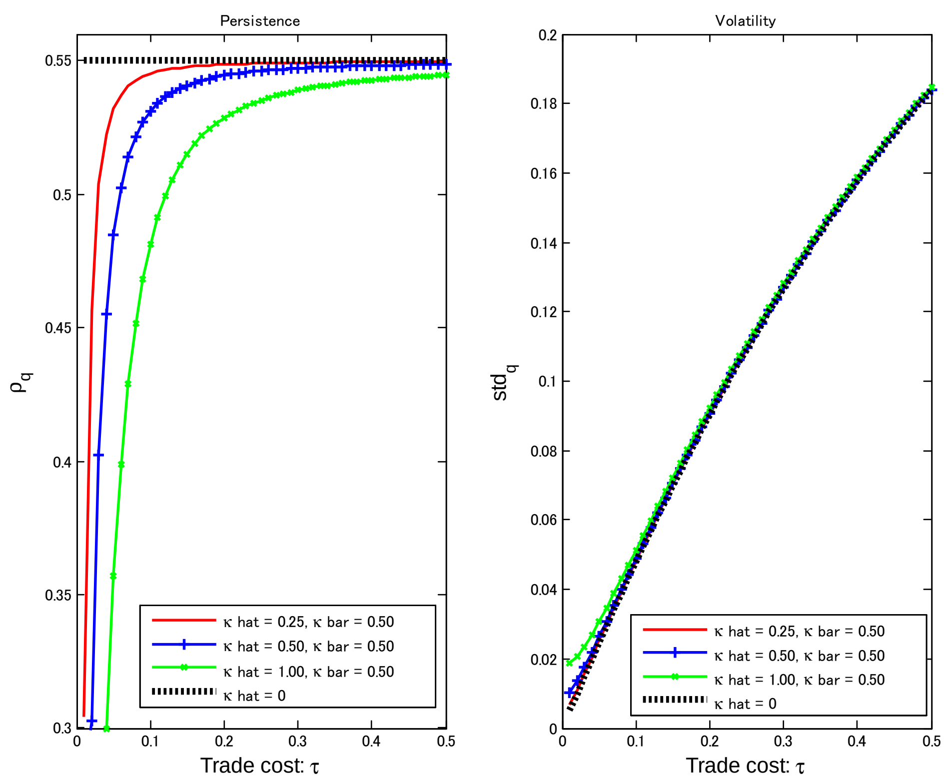

Figure 2: Effect of average information precision $\bar{\kappa}$ on persistence and volatility of LOP deviations

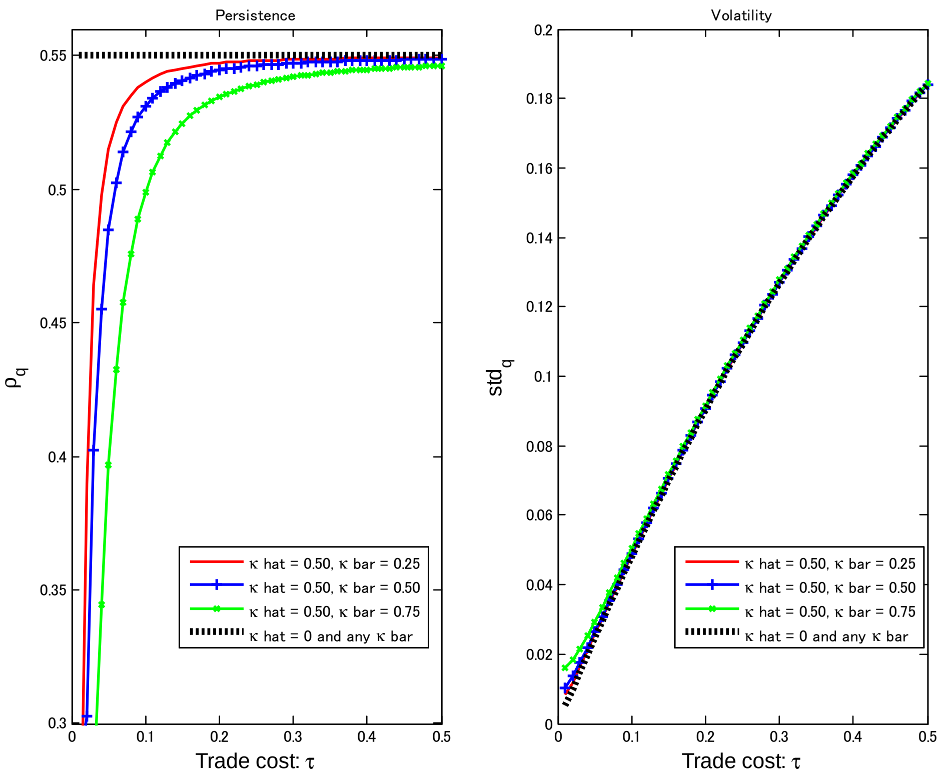

Figure 3: Effect of pricing complementarities α on persistence and volatility of LOP deviations

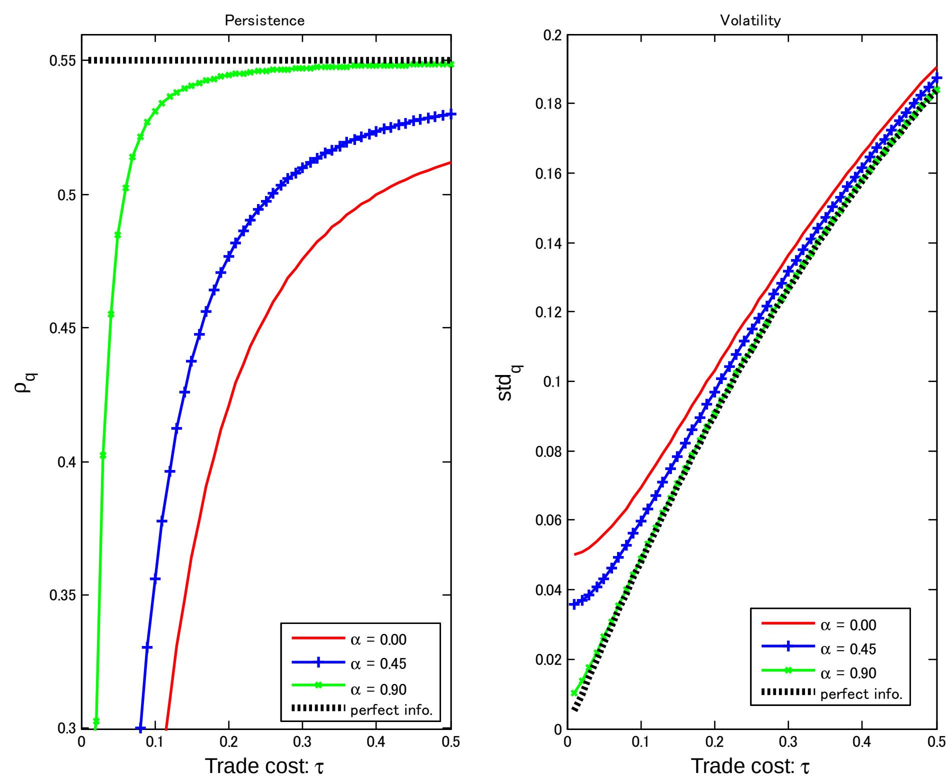

Figure 4: Introducing sticky prices

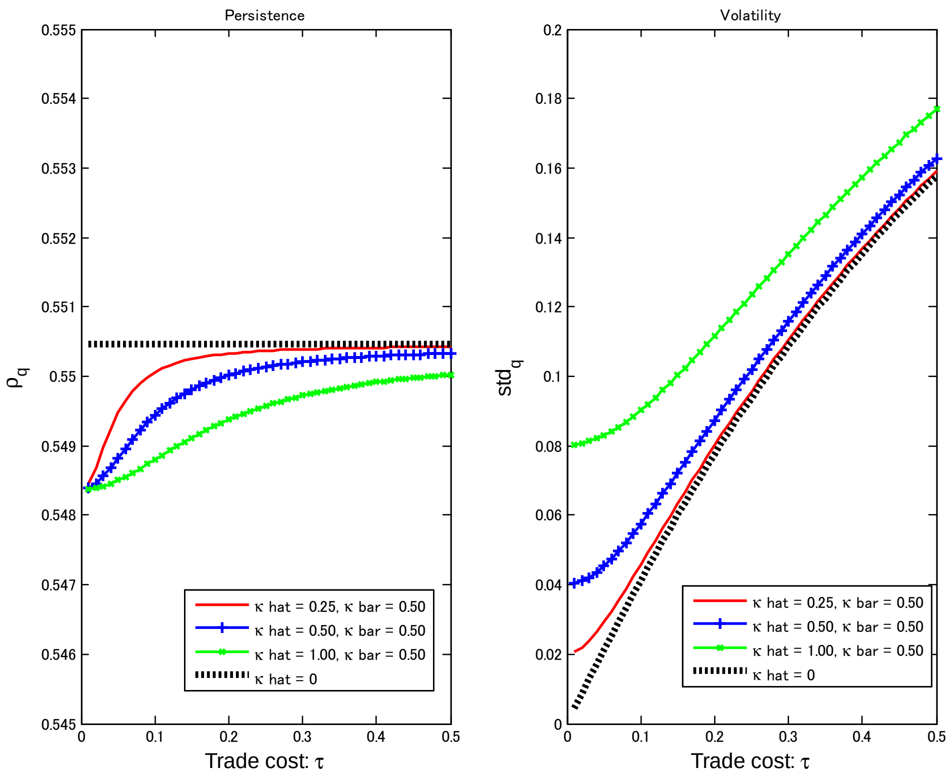

Figure 5: Multi-city model