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Noisy Information, Distance and Law of One Price Dynamics Across US Cities*

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Abstract

Using US micro price data at the city level, we provide evidence that both the volatility and the persistence of deviations from the law of one price (LOP) are rising in the distance between US cities. A standard, two-city, stochastic equilibrium model with trade costs can predict the relationship between volatility and distance but not between 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 show that the main predictions of the model continue to hold even if we allow for the interaction of imperfect information, sticky prices, and multiple cities.

JEL codes: E31, F31, D40

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1 Introduction

Trade costs still matter even among highly integrated economies. The empirical trade literature has shown a negative relationship between bilateral trade flows and distance to be robust across time and countries (see Disdier and Head, 2008). More recently, Anderson and van Wincoop (2004) survey the empirical literature on the law of one price (LOP) and emphasize the observed positive correlation between LOP deviations and distance. These correlations are across countries, and are consistent with a broad range of static trade theories in which distance proxies for trade costs.[1] The international macroeconomics literature has emphasized the time series properties of LOP deviations, specifically, their volatility and persistence. Most notably, Engel and Rogers (1996) and Parsley and Wei (2001) find a positive correlation between the time-series volatility of LOP deviations and distance. This correlation can be explained by using a variety of dynamic stochastic general equilibrium models of trade. For example, Crucini, Shintani, and Tsuruga (2010a, hereafter CST) develop a simple sticky price model where intra-national LOP deviations are driven by time-varying productivity to account for the positive correlation between the time-series volatility and trade costs. In contrast to the volatility-distance correlation, less is known about 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 model developed by CST, which can produce a positive volatility-distance correlation, fails to predict a positive persistence-distance correlation. This paper extends the dynamic model of CST to incorporate imperfect common knowledge as developed by Woodford (2003), Angeletos and La'O (2009), among others.

In the macroeconomics literature, it has been widely argued that heterogeneous expectations help to generate more plausible predictions about the inflation-output trade-off than homogeneous expectations. Mankiw and Reis (2002) and Woodford (2003) extend the homogenous expectations models of Lucas (1972) and Phelps (1970) by introducing (i) heterogenous

[1] For example, these can be obtained either by a variant of a static Ricardian model of Eaton and Kortum (2002) or by the static trade model of Helpman, Melitz and Rubinstein (2008) which emphasizes the self-selection of firms into export markets. See also Kano, Kano and Takechi (2013).

[2] Persistence of the real exchange rates, per se, has long attracted the attention of economists, with the estimate of half-lives of purchasing power parity deviations in the range of 3 and 5 years of half-lives. See Frankel (1986), Rogoff (1996), and Lothian and Taylor (1996).

expectations with strategic complementarities in firm's decision making under monopolistic competition and (ii) nominal aggregate demand shocks which cannot be common knowledge 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. We modify the 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 when information precision is heterogenous across cities, our two-city model produces a positive correlation between persistence and distance while preserving the prediction of the positive volatility-distance correlation produced by standard perfect information models. Our results are robust to extensions that include sticky prices or more than two cities.

The intuition for our result is that intra-national LOP deviations with imperfect information consist of two components: differences in productivity across locations and differences in information about nominal shocks across locations. In our model the difference in perception about demand across locations disappears after one period whereas productivity differences persist. Consequently, the persistence of LOP deviations is determined by the relative importance of the two components. A positive productivity shock in one location generates a LOP deviation 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 a persistent productivity difference becomes large and LOP deviations become more persistent. This implies a positive correlation between trade costs and persistence of LOP deviations.

Below, we begin with empirical evidence in Section 2. In Section 3, we present the theoretical model and investigate its implications for LOP dynamics. In Section 4, we discuss robustness of the results. Section 5 concludes.

2 Regressions

In this section, we provide evidence on the positive persistence-distance correlation, based on the US price data.

2.1 Data

We use quarterly data on 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).[3]

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 difference between the logarithm of the price of good i in city j and that 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 all $j, k = 1, 2, ..., 52$ with $j \neq k$. Because the number of cities is 52, the total number of city pairs is 1,326 in our data set.

For each of 63,648 ($48 \times 1,326$) series of relative prices, we compute persistence measures along with volatility measures, which are summarized in Table 1. Our persistence measures of $q_{j,k,t}(i)$ are: (i) the first-order autocorrelation, (ii) the sum of autoregressive coefficients (SAR), and (iii) the largest autoregressive (AR) root. The latter two persistence measures are computed by estimating univariate AR(p) models of $q_{j,k,t}(i)$ for each good and city pair separately (running 63,648 autoregressions in total).[4] The first three rows in the left panel of the table report the summary statistics for the persistence measures of $q_{j,k,t}(i)$ together with the standard deviations between 48 goods and across the entire sample. The full sample averages are: 0.52 for the first-order autocorrelation, 0.53 for the SAR, and 0.54 for the largest AR root. These estimates are consistent with other studies that find persistence is lower when micro-price data is used in place of CPI data. We also report the volatility measures used by Parsley and Wei (1996) in their study of ACCRA *Cost of Living Index* over 1975:Q1 - 1992:Q4. The volatility measures, tabulated in the right panel, are the standard deviation (sd_q) and the mean absolute price difference ($mapd_q$), where the latter measure is defined as

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

[4] We compute the first-order autocorrelation simply by estimating a coefficient in an AR(1) model. For the SAR and the largest AR root, we select lag lengths of AR models based on the Bayesian Information Criterion (BIC).

the time average of $|q_{j,k,t}(i)|$. Pooling all goods and bilateral pairs, the standard deviation is 0.136 and the mean absolute price difference is 0.158. Both of these are close to their counterparts in Parsley and Wei (1996), suggesting some robustness of these measures over time.

Table 1 also reports persistence and volatility measures of LOP deviations for city pairs whose locations are very close and very far apart. The fourth to sixth rows of the table report the persistence and volatility for 13 city pairs in which the distance between cities is less than 100 miles. Both persistence and volatility take values below the averages using all bilateral city pairs. In contrast, when we pick 76 city pairs in which the distance between cities is more than 2,000 miles, the averages of the persistence and volatility are above the averages using all bilateral city pairs. The contrast of these nearby and distant city pairings suggests that the persistence and volatility of LOP deviations are positively correlated to the distance separating the cities. In the next sub-section, we formally examine this relationship by means of regression analysis.

2.2 Regression results

The existing literature has assigned an important role for trade costs in the determination of LOP volatility. Specifically, Engel and Rogers (1996), Parsley and Wei (1996, 2001), among many others, have found that the LOP volatility is positively associated with the distance separating city pairs, a proxy for the trade cost. The well-known volatility-distance correlation is also confirmed in our dataset. When we pool all goods and run the volatility-distance regression using two volatility measures reported in Table 1 with good-specific dummies, the coefficients on the logarithm of distance are found to be positive and significant and the magnitudes of coefficients are broadly in line with the previous studies such as Parsley and Wei (1996).[5]

The main focus of our analysis is the persistence-distance relationship. That is, we run the same basic regression, but with persistence replacing volatility as the regressor:

$$\rho_{q_{j,k}}(i) = a(i) + b \ln dist_{j,k} + u_{j,k}(i),$$

where $\rho_{q_{j,k}}(i)$ is the first-order autocorrelation of LOP deviations of good i between cities j

[5] In particular, the coefficient estimates are 0.008 with the standard errors (clustered by city pairs) of 0.0004 when the dependent variable is sd_q and 0.03 with the standard errors of 0.002 when the dependent variable is $mapd_q$.

and k, $\ln dist_{j,k}$ is the logarithm of the great-circle distance between cities j and k, $a(i)$ is the good-specific fixed effect, and $u_{j,k}(i)$ is the regression error. For robustness, we also use SAR and the largest AR root as the regressand.

Table 2 reports the persistence-distance regression results for a variety of specifications. Specification (1) is the benchmark specification based on the above equation. The results show significantly positive correlations between all persistence measures and distance, based on standard errors clustered by city pairs reported below the estimates.[6] Suppose the distance between the cities increases from 100 miles to 2,000 miles. Using the result of the first-order autocorrelation, the coefficient estimate of 0.02 implies that the LOP persistence is increased by 0.06 ($= 0.02 \times \ln(2,000) - \ln(100)$).The increment in persistence is essentially the same when we use the SAR or the largest AR root.

Specification (2) in Table 2 replaces the good-specific effects with the distribution cost shares used in Crucini and Shintani (2008) who find that goods with higher distribution cost shares exhibit higher LOP persistence.[7] The distribution share is the wedge between what final consumers pay and what producers receive. These distribution costs include retail costs, markups and taxes. The distribution share can be used as an alternative measure of nontradability and, in fact, is included in the trade cost measures reported in Anderson and van Wincoop (2004). Our distribution shares are constructed based on sectoral US data aggregated to the national level. Therefore, our distribution shares vary across items but not across city pairs. Since the distance and distribution share are orthogonal to each other by construction, the coefficient on distance is essentially unaltered from the benchmark specification (1). Consistent with the previous finding, the estimated coefficients on the distribution share are all positive and significant. The estimates indicate that the goods and services with higher distribution shares have significantly slower speed of adjustment. The estimated coefficients range between 0.26 and 0.34, depending on what regressand is used. This additional regression confirms a positive relationship between trade cost and persistence when trade costs are proxied either by the distance which captures city-pair variation or by the distribution share which captures good-specific variation.

In specifications (3) and (4), we perform the robustness analysis by including the degree of price stickiness in the regressions. These specifications are in the spirit of earlier studies emphasizing the effect of price stickiness on persistence of good-level real exchange rates or

[6] We also confirmed that the coefficients on distance were statistically significant based on standard errors clustered by goods.

[7] We compare the items from EIU's *Worldwide Cost of Living Survey* used in Crucini and Shintani (2008) with those from ACCRA dataset and construct the distribution share variable for our regression analysis.

LOP deviations (e.g., Kehoe and Midrigan 2007, Crucini, Shintani, and Tsuruga 2010b, and Carvalho and Nechio 2011). These studies show theoretically (and confirm empirically) that LOP persistence is rising in the degree of price stickiness. Here, we measure the good-level degree of price stickiness as the probability of no price change at a quarterly frequency measured by $(1 - f_i)^3$, where f_i is the monthly frequency of price changes reported by Nakamura and Steinsson (2008).[8] Again, in both specifications, (3) and (4), the coefficient on distance is essentially unaltered from the benchmark specification (1). The coefficients on the distribution share in specification (4) decrease somewhat, but remain positive and statistically significant. We also note that the coefficient on the degree of price stickiness has the expected sign.

Our findings on the relationship between persistence and distance are broadly consistent with the few existing previous works. For example, Parsley and Wei (1996) report positive coefficients on the interaction terms of lagged relative prices and distance in augmented Dickey-Fuller regressions of relative prices between pairs of US cities. Their results imply that the convergence rate, measured by the SAR, is slower between cities that are further apart. Obstfeld and Taylor (1997) use disaggregated CPI data from 32 countries and US and Canadian cities and estimate a threshold autoregressive (TAR) model with the price difference following a random walk within the band of arbitrage but converging to the level of trade cost from outside the band. They regress the estimated threshold on distance and find a weak positive relationship between persistence and distance because observed persistence typically becomes higher when the band of inaction widens.[9] 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 SAR and half-lives are positively correlated with distance. Choi and Matsubara (2007) investigate sector-level price difference among Japanese cities from 1970 to 2002. They find that, for 22 out of 36 items, the estimated half-lives are positively correlated with distance after controlling for population differences. Although estimation results from previous works described above may not be directly comparable to ours due to the difference in data and methods, the positive relationship between persistence and distance has been gaining empirical support in the literature.

[8] 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 1988 - 2005. For regressions, we matched the Entry Level Items in the CPI with items in the ACCRA *Cost of Living Index*.

[9] See also Michael, Nobay, and Peel (1996), O'Connell (1998) and Taylor (2001).

3 Model

A natural question to ask is whether empirically tractable models of intra-national LOP deviations are consistent with the observed positive correlation between persistence and distance, as well as the observed positive correlation between volatility and distance. Our starting point is the two-city model developed by CST which predicts the volatility-distance correlation, but not the persistence-distance correlation. Next, we develop a model with imperfect information about demand across locations to capture both correlations. Numerical examples are provided to show the empirical relevance of the model. Finally, some extensions of the baseline model are developed and discussed to show the robustness of the model's predictions.

3.1 The limit of the perfect information model

In the CST model, firms in a city have a city-specific labor productivity and the difference in the logarithm of labor productivity $z_t(i)$ drive the short-run fluctuations of the inter-city LOP deviations $q_t(i)$. Let β be the discount factor satisfying $0 < \beta < 1$. 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

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

where s is the steady state expenditure share on home-made goods, or the "home bias" parameter satisfying $s > 1/2$. In the CST model, this home bias parameter s is given by

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

where τ (> 0) is the trade cost and ξ (> 1) is the elasticity of substitution across varieties. Note that s is an increasing function of τ and ξ.

The home bias parameter plays an important role in determining $q_t(i)$. 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 actually 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 τ.

One might think that infrequent information updating, referred to as sticky information by Mankiw and Reis (2002), could explain the positive persistence-distance correlation. Crucini, Shintani, and Tsuruga (2010b) show that if firms cannot update their information set with a probability ω, which is common across firms in the economy, $q_t(i)$ 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, the persistence of $q_t(i)$ is independent of trade cost τ. Although less frequent information updating (a larger ω) increases the persistence, once again this occurs irrespective of the trade cost, τ.

3.2 A noisy information model

This section takes the flexible price version of the perfect information model of CST and adds noisy information about aggregate nominal expenditure to explain the positive persistence-distance correlation. We assess the models' ability to replicate the observed magnitude of the positive regression coefficient on distance for reasonable parameter values in a calibration exercise.

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 $P_t = \left[\int_0^1 P_t(i)^{1-\xi} di\right]^{1/(1-\xi)}$.[10]

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

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

where ε_t^θ is independently and identically distributed. 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 inputs of composite intermediate goods, and labor, 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 composites 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

[10] One can also consider an alternative sequence of aggregations which interchanges the aggregation across cities j and the aggregation across goods i. While this allows for the general price indexes at the city level, such a change in the sequence of aggregation does not affect results in this paper.

clearing conditions for each brand of each good satisfy

$$\begin{aligned}
Y_t(i,v) &= C_{1,t}(i,v) + \Gamma_{1,t}(i,v) + (1+\tau)\left[C_{2,t}(i,v) + \Gamma_{2,t}(i,v)\right] \quad \text{for } v \in [0,1] &(5)\\
Y_t(i,v) &= (1+\tau)\left[C_{1,t}(i,v) + \Gamma_{1,t}(i,v)\right] + C_{2,t}(i,v) + \Gamma_{2,t}(i,v) \quad \text{for } v \in (1,2]. &(6)
\end{aligned}$$

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

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:

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

where the productivity in city ℓ, in the production of good i, namely $z_{\ell,t}(i)$, follows a stationary ARMA process.

$$A_\ell(i,L)\, z_{\ell,t}(i) = B_\ell(i,L)\, \varepsilon^z_{\ell,t}(i), \qquad \varepsilon^z_{\ell,t}(i) \sim N(0, \sigma_z^2(\ell)). \tag{8}$$

where $A_\ell(i,L)$ and $B_\ell(i,L)$ are lag polynomials for AR and MA components which differ across goods and the place of production. We further assume that $\sigma_z^2(\ell)$ is location specific such that the productivity innovations for good i are independently drawn from a distribution with a location-specific variance. Using these assumptions, we allow for the possibility that persistence and volatility of $z_{\ell,t}(i)$ are both good- and location-specific. Throughout this paper, we measure the persistence of $z_{\ell,t}(i)$ by the first-order autocorrelation $\rho_{z,\ell}(i)$ and assume that $0 < \rho_{z,\ell}(i) < 1$ for $i \in [0,1]$ and $\ell = 1, 2$.

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

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

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 $\varepsilon^x_{j,t}(i,v)$ are independently drawn from a distribution with a location-specific variance. This reflects the assumption that retail managers are isolated in city j in terms of their information and receive idiosyncratic signals of nominal aggregate demand with different levels of precision.

In stage 2, 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: the information set differs across j (i.e., where retail managers live), good i and brand v. As in Angeletos and La'O (2009), we assume that θ_t becomes common knowledge after one period. We later discuss the possibility of replacing this assumption with an alternative information structure such that agents learn the exact value of θ_t only in the limit, as time goes to infinity.

In the baseline model, we assume flexible prices for all goods to focus attention on the 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 expectation 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.[11]

The 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

[11] 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 $j = k$ and $j \neq k$.

expenditure share s represents the degree of expenditure bias toward home-produced goods. According to (12), this home bias makes the home city price index more sensitive to the 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

Our interest is to see whether the persistence of LOP deviations depends on trade costs, τ, and therefore on distance. As emphasized in Kehoe and Midrigan (2007) and CST, both the strategic complementary parameter α and the productivity persistence parameter $\rho_{z,\ell}(i)$ play an important role in explaining the persistence of LOP deviations. In addition to these two parameters, our model adds a third key parameter, $\hat{\kappa}$, the Kalman gain difference between retail managers which captures the information differences. This asymmetric noisy information structure allows us to account for the persistence-distance correlation.

Expectations about aggregate nominal demand are formed using a standard signal extraction problem

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

where κ_j is the steady-state Kalman gain defined as $\sigma_\theta^2/\left[\sigma_\theta^2 + \sigma_x^2(j)\right]$. The smaller is the noise, $\sigma_x^2(j)$, the clearer is the signal, κ_j.

The model is solved utilizing the method of undetermined coefficients.[12] 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 and c_1 are undetermined coefficients. Given the guess for p_t, combining (11) – (13) yields

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

Note that the integration over the individual signals eliminates the idiosyncratic noise $\varepsilon_{j,t}^x(i,v)$. The relative price $q_t(i) \equiv p_{2,t}(i) - p_{1,t}(i)$ can be shown to equal

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

where $\phi = (1-\alpha)\hat{\kappa}/(1-\alpha\bar{\kappa})$, $\bar{\kappa} = (\kappa_1+\kappa_2)/2$, $\hat{\kappa} = \kappa_2 - \kappa_1$, and $z_t(i) = z_{1,t}(i) - z_{2,t}(i)$. Note that $\bar{\kappa}$ may be interpreted as the level of information precision in the macroeconomy and $\hat{\kappa}$ is a measure of the spatial dispersion of information precision between the two cities.

[12] We leave the detailed derivation in Appendix A.1 and focus on key equations in the main text.

For ease of exposition, $\hat{\kappa}$ is referred to as the information difference, which is one of the key parameters of the model. Without loss of generality, let $\kappa_1 \leq \kappa_2$ so that $\hat{\kappa} \geq 0$. Finally, $z_t(i)$ represents the productivity difference between two cities.

As shown in (15), the two driving forces of LOP deviations are: i) the aggregate nominal demand shock ε_t^θ and ii) the productivity difference between two cities $z_t(i)$.[13] To see why ε_t^θ matters for $q_t(i)$, suppose productivity is equal across cities so that $z_t(i) = 0$. Since managers receive signals of different precision as measured by $\sigma_x^2(j)$, they set different prices in response to the same shock to nominal aggregate demand. This gives rise to an LOP deviation that lasts for one period because ε_t^θ is assumed to be fully revealed to all managers in the next period.[14]

LOP deviations are also driven by the productivity difference, $z_t(i)$. To understand how $z_t(i)$ affects LOP deviations, suppose that productivity in city 1 increases by one percent. The productivity improvement in city 1 decreases the price of index in city 1 by larger amount than the price index in city 2 due to the home bias in expenditure shares arising from trade costs (i.e., $s > 1/2$). The coefficient $(2s - 1 > 0)$ on the productivity difference, $z_t(i)$, is increasing in the size of the trade cost and the substitutability of varieties. Given the linear relationship between $q_t(i)$ and $z_t(i)$, the LOP deviation has the same persistence properties as the productivity difference.

Note that, given the independence of $z_{1,t}(i)$ and $z_{2,t}(i)$, the variance of $z_t(i)$ is simply the sum of variances of the location-specific productivity (i.e., $var[z_t(i)] = var[z_{1,t}(i)] + var[z_{2,t}(i)]$). Consequently, the first-order autocorrelation of $z_t(i)$ can be expressed as a weighted average of the first-order autocorrelations of the location-specific productivities:

$$\rho_z(i) = \frac{var[z_{1,t}(i)]}{var[z_t(i)]}\rho_{z,1}(i) + \frac{var[z_{2,t}(i)]}{var[z_t(i)]}\rho_{z,2}(i). \tag{16}$$

Using equation (15), the standard deviation of the LOP deviation is $sd_q(i) = \sqrt{var[q_t(i)]}$

[13] Note that $q_t(i)$ in (15) can always be approximated by the AR(p) process with a large p. This justifies the use of the AR(p) model in computing the persistence measures in Section 2. For example, when $z_{1,t}(i)$ and $z_{2,t}(i)$ follow an AR(1) with common persistence parameter $\rho_z(i)$, $q_t(i)$ can be expressed as an ARMA(1,1) process given by $q_t(i) = \rho_z(i)\, q_{t-1}(i) + e_t(i) + \delta(i) e_{t-1}(i)$, where $\delta(i)$ is $-(2\rho_z(i))^{-1}\left[1 + [\rho_z(i)]^2 + (2s-1)^2 \sigma_z^2/\left(\phi^2\sigma_\theta^2\right)\right] + (2\rho_z(i))^{-1}\left[\sqrt{1 + [\rho_z(i)]^2 + (2s-1)^2 \sigma_z^2/\left(\phi^2\sigma_\theta^2\right) - 4[\rho_z(i)]^2}\right]$ satisfying $|\delta(i)| < 1$. This implies that $q_t(i)$ can also be expressed as an AR(∞) process.

[14] A more general treatment would allow for the presense of persistent informational deficiencies, as in the case of Mankiw and Reis (2002) and Woodford (2003), the nominal shocks will have a longer effect.

where

$$var\left[q_t\left(i\right)\right]=\phi^2\sigma_\theta^2+(2s-1)^2 var\left[z_t\left(i\right)\right] \ . \tag{17}$$

Notice that the variance of LOP deviation is bounded from below by the variance of the productivity difference (multiplied by $(2s-1)^2$) and is rising in the information differences.

The first-order autocorrelation of $q_t\left(i\right)$ is given by

$$\rho_q(i)=\frac{(2s-1)^2 var\left[z_t\left(i\right)\right]}{\phi^2\sigma_\theta^2+(2s-1)^2 var\left[z_t\left(i\right)\right]}\rho_z(i). \tag{18}$$

Notice that the persistence of LOP deviation is bounded from above by $\rho_z(i)$ and is falling in the extent of the information differences across retail managers.[15]

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

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

(i) *volatility measured by sd_q is increasing in the trade cost τ,*

$$\frac{\partial sd_q\left(i\right)}{\partial\tau}>0;$$

(ii) *persistence measured by $\rho_q(i)$ is independent of the trade cost τ when information about nominal aggregate demand, θ_t, is perfect (i.e., $\sigma_x(1)\rightarrow 0$ and $\sigma_x(2)\rightarrow 0$) or when information on θ_t is imperfect and information difference between managers in different cities is absent (i.e., $\hat{\kappa}=0$),*

$$\frac{\partial\rho_q(i)}{\partial\tau}=0;$$

(iii) *persistence measured by $\rho_q(i)$ is increasing in the trade cost τ when information about θ_t is imperfect and information difference between managers in different cities is present (i.e., $\hat{\kappa}\neq 0$),*

$$\frac{\partial\rho_q(i)}{\partial\tau}>0.$$

The proposition implies that, when trade costs rise with the distance separating locations, the model with perfect information can account for the positive volatility-distance correlation

[15] Appendix A.2 provides the derivations of (16) – (18).

discovered by the literature, but fails to predict the positive persistence-distance correlation. In contrast, the presence of an information difference across managers in different cities can account for both observations.[16]

To see the intuition for part (i) of Proposition 1, again suppose that there is a one percent increase in the location-specific productivity of city 1. If the 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 the 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.

Let us now turn to part (ii) of Proposition 1. With perfect information, the effect of a change in θ_t on the price indexes in two cities cancels out because managers increase prices by the same amount in two cities. The same intuition applies to the case of the imperfect information without information difference. Because the same information precision of uninformed managers implies price increases by the same amount, in response to an increase in θ_t, the effect on the price indexes cancels out. In either of these cases, the relative prices are solely determined by the productivity differences and the persistence of $q_t(i)$ corresponds to the persistence of $z_t(i)$ which is independent of the trade cost.

The result of part (iii) of Proposition 1 can be explained as follows: When imperfect information is present with asymmetric information precision across managers in different cities, the persistence of $q_t(i)$ is bounded between zero, the i.i.d. process ε_t^θ, and $\rho_z(i) > 0$, the persistence of the productivity difference, $z_t(i)$. In the trivial case in which the home bias is zero ($s \to 1/2$), the LOP deviations do not depend on productivity differences because productivity shocks transmit symmetrically to all locations of sales. Thus, LOP deviations become i.i.d., being determined solely by innovations to aggregate nominal expenditure. As trade costs become larger, home bias increases ($s > 1/2$) and the contribution of the productivity difference to persistence rises. Indeed, the persistence of LOP rises from zero toward $\rho_z(i)$ as the productivity channel increases in importance relative to the demand channel (see (18)).

Two additional remarks are useful at this point. First, it is of interest to see if the results in Proposition 1 continue to hold when Angeletos and La'O's (2009) assumption of short-

[16] As pointed out by an anonymous referee, Proposition 1 holds even if the assumption of heterogeneous information across retail managers given by (9) is replaced by the assumption of the homogeneous information given by $x_{j,t}(i,v) = x_{j,t} = \theta_t + \sigma_x^2(j)\,\varepsilon_t^x$, where $\varepsilon_t^x \sim N(0,1)$. However, in such a case, dynamics of $q_t(i)$ will become more complicated and cannot be described simply by (15).

lived informational deficiencies is replaced by more persistent informational deficiencies, as in Mankiw and Reis (2002) and Woodford (2003). As long as informational deficiencies are less persistent than the productivity difference, all the results remain valid. If $\bar{\kappa}$ is relatively large or α is relatively small, this condition is likely to be met under typical speed of informational deficiency adjustment considered in the modern imperfect information literature. Second, $z_t(i)$ disappears from (15) if the productivity $z_{\ell,t}(i)$ is common across two cities. Even when $z_t(i)$ is absent, if the model has city-specific preference shocks biased toward home goods and if the preference shocks in the two cities are persistent, the same qualitative results as in Proposition 1 can be obtained.[17] In this sense, our results do not critically depend on the assumption of the location-specific productivity.

3.4 Numerical examples

In the previous section, persistence of $q_t(i)$ was demonstrated to be positively associated with trade costs in the noisy information model. At the same time, equation (18) shows that three key parameters ($\hat{\kappa}$, α, $\rho_z(i)$) determine the level of LOP persistence that arises in equilibrium. The purpose of this section is to provide some assessment of the empirical relevance of the theory. The starting point is to provide analytical results showing how $\rho_q(i)$ changes over a plausible range of trade cost in the noisy information model. In particular, how does $\rho_q(i)$ change as a function τ for various settings of $\hat{\kappa}$, α, and $\rho_z(i)$, keeping the other parameters $\bar{\kappa}$, ξ, and $var[z_t(i)]/\sigma_\theta^2$ constant? With this analysis in hand, the model is evaluated based on its ability to replicate the estimated coefficient on distance in our persistence-distance regressions.

Beginning with the parameters whose values are kept constant throughout our analysis, the average of the Kalman gains across managers, is set to $\bar{\kappa} = 0.5$, the benchmark value employed by Angeletos and La'O (2009) in their simulations. Conveniently, this makes $\hat{\kappa}$ lie on the unit interval $[0, 1]$. At one extreme is $\hat{\kappa} = 0$, where the noise-to-signal ratio is common across managers: $\sigma_x^2(1)/\sigma_\theta^2 = \sigma_x^2(2)/\sigma_\theta^2 = 1$. The other extreme is $\hat{\kappa} = 1.00$, where one manager has no information about the shocks to θ_t while the other receives a perfect signal: $\sigma_x^2(1)/\sigma_\theta^2 = \infty$ and $\sigma_x^2(2)/\sigma_\theta^2 = 0$. The elasticity of substitution across goods is set to $\xi = 4$, a value taken from Broda and Weinstein (2006). Note that (18) implies that the persistence depends on the variance ratio, $var[z_t(i)]/\sigma_\theta^2$. We follow Crucini, Shintani, and Tsuruga (2013) and set $\sqrt{var[z_t(i)]/\sigma_\theta^2} = 5$.[18]

[17] Details of this result is provided in Appendix A.3 which is available upon request.

[18] One of benchmark values of the standard deviation ratio of real shock to nominal shock was 5 in their

Grossman (1998) and Hummels (2001), among others, specify the relationship between trade costs and distance as a power function

$$\tau = c \times dist^{\delta} \tag{19}$$

where $dist$ is the distance between two locations, δ is the elasticity of τ with respect to distance and c is a constant. Following Anderson and van Wincoop (2004), we set $\delta = 0.30$, a consensus value in the empirical trade literature. If we assume that the average distance from the data in our regression analysis corresponds to the typical trade cost value $\bar{\tau} = 0.20$ taken from the value used in CST, our sample implies the range of trade cost, $\tau \in [0.07, 0.30]$.[19]

Turning to the key parameters, $\hat{\kappa}$, α, and $\rho_z(i)$, a wide range of parameters is considered. The information difference ranges upward from a base of no difference, $\hat{\kappa} = 0$, 0.20, 0.50, and 0.80. Strategic complementarities include the values: $\alpha = 0.00$, 0.45, and 0.90. As shown in (18), the model suggests that $\rho_z(i)$ is the upper bound for $\rho_q(i)$ which is an increasing function of the trade cost. The lower panel of Table 1 shows that the LOP persistence for city pairs in which cities are the farthest apart is 0.56 with the between-good standard deviations of 0.15. The persistence of productivity differences that encompasses this level of LOP persistence: $\rho_z(i) = 0.30$, 0.60, and 0.90.

Figure 1 shows the relationship between $\rho_q(i)$ and $\ln \tau$, as well as the relationship between sd_q and $\ln \tau$, and their sensitivity to $\hat{\kappa}$, when the other two key parameters are set at $\alpha = 0.00$ and $\rho_z(i) = 0.60$. The patterns confirm the properties proven in Proposition 1. The right panel of the figure shows that, regardless of values of information difference, the volatility of LOP deviations depends positively on $\ln \tau$.[20] In contrast, the curves for persistence in the left panel are upward-sloping only when $\hat{\kappa}$ is non-zero. If $\hat{\kappa} = 0$, the persistence curve is flat, independent of trade costs and equal to the persistence of the productivity difference, $\rho_z(i) = 0.60$. An increase in $\hat{\kappa}$ can be interpreted as a larger information difference 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 difference increases the importance of the i.i.d.

analysis of international LOP. They claim that the value of 5 matches well with their data, compared to alternative values of 1 and 1/5.

[19]Based on the US data, Anderson and van Wincoop (2004) estimate that total international frictions average 74 percent. These frictions are further divided into those arising from transportation costs amounting to a wedge of 0.21 percent and a border-related wedge 0.44 ($0.74 = 1.21 \times 1.44 - 1$). Due to the absence of the international border in our model, our choice of $\bar{\tau} = 0.20$ seems reasonable for an average across bilateral city pairs.

[20]The volatility curve is drawn by fixing σ_θ^2 at 0.01 along with the assumption of $\sqrt{var\left[z_t(i)\right]/\sigma_\theta^2} = 5$.

nominal demand shock relative to the persistent productivity difference in the determination of the LOP deviations.

Figure 2 shows persistence and volatility and their sensitivity to α, when the other two key parameters are fixed at $\hat{\kappa} = 0.50$ and $\rho_z(i) = 0.60$. 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. We show that strategic complementarities also affect both the persistence and volatility of relative prices across locations. Stronger strategic complementarities raise the persistence of LOP deviations 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.

Finally, Figure 3 shows persistence and volatility and their sensitivity to $\rho_z(i)$, when other two key parameters are set at $\alpha = 0.00$ and $\hat{\kappa} = 0.50$. Not surprisingly, the left panel of the figure shows the higher $\rho_z(i)$ corresponds to the higher $\rho_q(i)$ since the latter is proportional to the former (see equation (18)). In contrast, the volatility of LOP deviations is the same for all $\rho_z(i)$ simply because $var[z_t(i)]$ and σ_θ^2 in (17) remain unchanged by changing $\rho_z(i)$.

While these figures are helpful in understanding the mechanism, further investigation is required to ask whether our model can reproduce the estimated coefficient on distance in our regression analysis. To answer this question, we calibrate the regression coefficient from the model based on the following procedure.

Note that our analysis in Section 2 employs a linear regression of LOP persistence on distance, whereas the first-order autocorrelation in (18) is non-linear in trade cost. We can first linearly approximate (18) around $\ln \bar{\tau}$, and then use (19) to transform the coefficient on trade cost to that on distance. This predicted coefficient on distance corresponds to the slope of persistence curve in Figures 1-3 evaluated at $\ln 0.20$ (≈ -1.61) multiplied by $\delta = 0.30$. While the slope depends on all the key parameters, $\hat{\kappa}$, α, and $\rho_z(i)$, we pay special attention to $\hat{\kappa}$ because the presence of information difference is the essential feature in producing the persistence-distance correlation in the noisy information model.

Panel A of Table 3 reports the coefficients on distance for various $\hat{\kappa}$, using the baseline two-city noisy information model for the purpose of matching the estimated coefficient of 0.02 in Table 2. Note that the standard errors reported in Table 2 imply that the 95 percent confidence interval of the estimated coefficient is given by [0.016, 0.024] (= [0.02−1.96×0.002, 0.02+1.96×0.002]). This provides lower and upper bounds for $\hat{\kappa}$, which are reported in the last three columns of the table. The first three rows in the panel show the predicted coefficients for different levels of strategic complementarity, $\alpha = 0.90$, 0.45, and 0.00, with $\rho_z(i)$ fixed at 0.60. When strategic complementarities are very strong, such as $\alpha = 0.90$, increasing the informational asymmetry has very little effect on the slope coefficient, resulting in the failure of the model to replicate the persistence-distance relation in the data. However, for smaller values of α, the model performs well over a reasonable range of $\hat{\kappa}$. For example, the predicted range of $\hat{\kappa}$ is $[0.45, 0.57]$ when $\alpha = 0.45$, while the predicted range is $[0.32, 0.41]$ when $\alpha = 0.00$. Thus, the information difference required for replicating the estimated coefficient becomes smaller, as the degree of strategic complementarities becomes lower.

Next two rows show the effects of changing $\rho_z(i)$, while keeping $\alpha = 0.00$. When $\rho_z(i) = 0.30$, the required level of $\hat{\kappa}$ increases compared to the benchmark case of $\rho_z(i) = 0.60$. In contrast, when $\rho_z(i) = 0.90$, the required level of $\hat{\kappa}$ decreases. This simply reflects the fact that the change of $\rho_z(i)$ has a proportional effect on the slope of $\rho_q(i)$ and the predicted coefficient. At the same time, the range of $\hat{\kappa}$ that is consistent with the data becomes wider as $\rho_z(i)$ becomes smaller.

4 Discussion

This section considers the robustness of our results to the presence of sticky prices or multiple cities. We will show that our results remain valid at least under some simplifying assumptions. Importantly, we show that the extended model can still replicate the estimated coefficients in the persistence-distance regressions.

4.1 The role of 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. In Section 2 we found that, even after controlling for the distribution share, LOP persistence was higher for goods whose prices changed less frequently (stickier prices). To this feature into account, 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 $1 - \lambda(i)$. To simplify the argument, let us assume $\alpha = 0$ and that $z_{1,t}(i)$ and $z_{2,t}(i)$ follow a common AR(1) process (i.e., $\rho_{z,1}(i) = \rho_{z,2}(i) = \rho_z(i)$ and $\sigma_z(1) = \sigma_z(2)$).

The LOP deviation from the noisy information model with sticky prices follows the first-order difference equation:[21]

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

This is easily compared to our flexible price model by setting $\lambda(i) = 0$, to arrive at $q_t(i) = \hat{\kappa}\varepsilon_t^{\theta} + (2s-1)z_t(i)$ and noting that the only difference between this equation and (15) is the absence of strategic complementarity ($\alpha = 0$), in which case $\phi = \hat{\kappa}$. Clearly as prices adjust less frequently ($\lambda(i)$ rises above zero) managers respond less to news about nominal aggregate demand. Thus, conditional on demand shocks, persistence is rising and conditional volatility is falling in the extent of price rigidity.

In our model, LOP deviations also originate from changes in relative productivity. The coefficient on $z_t(i)$ is still increasing in trade cost, due to the presence of $(2s-1)$. However, the effect of sticky prices mitigates the productivity channel even further than is the case for the nominal demand shock through the coefficient $[1-\lambda(i)\,\beta] / [1-\lambda(i)\,\beta\rho_z(i)]$ which is strictly less than one. Because of this similarity, the results in Proposition 1 continue to hold for the sticky price case. In other words, the higher trade cost still gives rise to more persistent $q_t(i)$ through larger home bias, though the quantitative implications are different.

Let us again investigate whether the noisy information model with sticky prices can quantitatively account for the regression results. The simple average of the degree of price stickiness across good used in our regression analysis is 0.65. This value of $\lambda(i)$ implies that prices remain fixed for 8.6 months on average, consistent with the findings of Nakamura and Steinsson (2008) who estimate the median duration of regular prices is 8 - 11 months. To account for substantial heterogeneity in the degree of price stickiness across goods, the cases of $\lambda(i) = 0.35$ and 0.95 are contrasted. Panel B of Table 3 reports the predicted regression slope from the noisy information model with sticky prices when $\alpha = 0.0$ and $\rho_z(i) = 0.6$. Other parameter values are same as the case of the baseline flexible price model. The results show that the model can replicate the estimated coefficient when $\lambda(i)$ is either 0.35 and 0.65. The range of $\hat{\kappa}$ consistent with the data becomes wider with sticky prices compared to the baseline flexible price model. However, when $\lambda(i)$ becomes as large as 0.95, the model fails to replicate the observed regression slope. This result follows from the prominent role frequency of price changes play in the sticky price model as described in (20), when $\lambda(i)$ is very high the term involving τ becomes negligible. In contrast, when $\lambda(i)$ is relatively small, dynamics

[21] Derivation of this equation is provided in Appendix A.4 which is available upon request.

of $q_t(i)$ given by (20) becomes more similar to that in the flexible price model given by (15) and the model can still explain the observed regression coefficient on distance.

4.2 Multi-city model

The baseline framework is a two-city model, whereas the data span numerous cities. This section considers an N city extension of the model. Beginning with the price index in a representative city (say city 1), we have

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

We derive the explicit solution for LOP deviations in the multi-city model where the trade cost can differ across city pairs.[22] In this multi-city model, we redefine the LOP deviations between cities 1 and 2 as $q_{2,1,t}(i) = \ln[P_{2,t}(i)/P_{1,t}(i)]$. We also denote $\tau_{\ell,j}$ by the iceberg transportation cost to carry goods from city ℓ to j, where $\tau_{\ell,j}$ satisfies the assumptions that $\tau_{\ell,j} = \tau_{j,\ell}$ and $\tau_{j,j} = 0$. Under flexible prices, $q_{2,1,t}(i)$ is given by

$$q_{2,1,t}(i) = \phi_{2,1}\varepsilon_t^{\theta} + \sum_{\ell=1}^{N}(s_{\ell,1} - s_{\ell,2})\, z_{\ell,t}(i), \tag{22}$$

where

$$\phi_{2,1} = \frac{(1-\alpha)\hat{\kappa}_{2,1}}{1-\alpha\bar{\kappa}} \tag{23}$$

$$s_{\ell,j} = \frac{(1+\tau_{\ell,j})^{1-\xi}}{\sum_{m=1}^{N}(1+\tau_{m,j})^{1-\xi}} \text{ for } j = 1,2 \text{ and } \ell = 1,2,...,N, \tag{24}$$

and $\bar{\kappa} = N^{-1}\sum_{j=1}^{N}\kappa_j$ and $\hat{\kappa}_{2,1} = \kappa_2 - \kappa_1$. Interestingly, $\bar{\kappa}$ is the average of information precision across all N managers while $\hat{\kappa}_{2,1}$ remains the spatial dispersion of information precision between two cities under examination. The parameter $s_{\ell,j}$ is the steady-state expenditure share of consumption in city j on goods produced in city ℓ. When $\ell = j$, this parameter can be understood as the home bias parameter as in the two-city model. Also, when $N = 2$, $s_{\ell,1} - s_{\ell,2}$ reduces to $2s - 1$ for $\ell = 1$ and $1 - 2s$ for $\ell = 2$. Hence, (22) generalizes (15) in the two-city model.

Compared to the case of only two cities, the LOP deviations still include both temporary

[22] Details of this derivation is provided in Appendix A.5 which is available upon request.

and persistent components and the coefficient for ε_t^θ remains effectively unchanged. However, there is no longer the productivity difference in (22). Instead, the productivity for each city contributes to dynamics of LOP deviations even when the relative price between cities 1 and 2 is considered. This is because the prices in cities 1 and 2 include prices of brands produced in all cities in the economy, as indicated in (21).

Let us assume that all $z_{\ell,t}(i)$ have a common variance and first-order autocorrelation (i.e., $\rho_{z,1}(i) = \rho_{z,2}(i) = \cdots = \rho_{z,N}(i)$ and $var[z_{1,t}(i)] = var[z_{2,t}(i)] = \cdots = var[z_{N,t}(i)]$). Then, the first-order autocorrelation of $q_{2,1,t}(i)$ is given by

$$\rho_{q,2,1}(i) = \frac{\psi^2 var[z_{1,t}(i)]}{\phi_{2,1}^2\sigma_\theta^2 + \psi^2 var[z_{1,t}(i)]}\rho_{z,1}(i), \tag{25}$$

where $\psi^2 = \sum_{\ell=1}^N (s_{\ell,1} - s_{\ell,2})^2$. The underlying structure of the LOP persistence shown in (25) is similar in structure to that under the two-city model (18). As long as ψ is increasing in $\tau_{1,2}$, the model can still explain a positive persistence-distance correlation.

Unfortunately, we cannot determine the sign of the derivative of ψ with respect to $\tau_{1,2}$ in general. Hence, the need for simulations. As in the previous exercise, we linearly approximate (25) around $\ln\bar{\tau}$ and use the relationship (19) for $\tau_{1,2}$ for the purpose of evaluating the model's ability of replicating the observed positive regression coefficient on the log-distance. For comparison purpose, we report the case of $N = 3$, $\alpha = 0.00$ and $\rho_{z,1}(i) = \rho_{z,2}(i) = \rho_{z,3}(i) = 0.60$ to see the marginal changes in results.[23]

Panel C of Table 3 shows the coefficients on distance for the three-city model for various values of $\hat{\kappa}$ (more precisely $\hat{\kappa}_{2,1}$). In both rows of the panel, the partial derivative of $\rho_{q,2,1}(i)$ with respect to the log distance is computed numerically. The first row of the panel assumes that the trade cost is the same across all three city pairs. Under this assumption, the information difference required for replicating the estimated coefficient on distance is smaller than in the two-city model, while the range of $\hat{\kappa}$ that is consistent with the data is narrower. The second row of the panel allows for different values of trade cost between cities 1 and 3 and between cities 2 and 3. Here, while $\tau_{1,2}$ remains unchanged at 0.20, $\tau_{1,3}$ and $\tau_{2,3}$ are set to 0.30 and 0.10, respectively, to keep the average trade cost unchanged at $\bar{\tau} = 0.20$.[24] Under this parameterization, the required level of $\hat{\kappa}$ becomes slightly higher than the case of symmetric trade costs and the range of $\hat{\kappa}$ is wider, but neither change is very substantial. Hence, our calibration results suggest that, within a reasonable range of parameter values,

[23] For the variance ratio of real and nominal shocks, we set $\sqrt{3 \times var[z_{1,t}(i)]/\sigma_\theta^2} = 5$.

[24] Note that these additional parameter values fall within the range of $\tau \in [0.07, 0.30]$ in the data.

the three-city model continues to imply a positive persistence-distance correlation and can still explain the observed regression coefficient. Similar results can be obtained even if we combine the multi-city model with sticky prices, as shown in Panel D of Table 3 with the choice of $\lambda(i) = 0.65$. To sum up, both the flexible price and sticky price three-city models suggest that the main predictions of the noisy information model are robust.

5 Conclusion

This paper studies micro price data across US cities to provide empirical evidence that persistence of intra-national LOP deviations are positively correlated with the distance between cities. To explain the empirical findings, we develop a model of time-varying productivity combined with imperfect information about aggregate nominal demand. Assuming that distance proxies trade cost between two cities, we found that the perfect information model can account for the observed positive volatility-distance correlation pointed out by the literature but fails to predict the observed positive persistence-distance correlation. In contrast, the noisy information model can account for both observations if there is an information difference across managers in different cities. The key mechanism is that shocks arising from imperfect information are temporary while shocks from productivity are long-lived. When 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. Under the perfect 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, while not ruling out other plausible mechanisms. For example, productivity spill-overs across manufacturers may be negatively correlated with distance. This could produce a positive persistence-distance correlation in LOP deviations. However, careful investigation of this requires highly disaggregated data on productivity, and as such, may be a promising direction for future research.

Appendix

A.1 Derivation of (15)

Our guess for the aggregate price index is given by

$$p_t = c_0\theta_t + c_1\theta_{t-1}. \tag{A1}$$

This conjecture is supported as follows: retail managers use the Kalman filter to make forecasts of θ_t in computing their own prices. As shown in (13), the forecast of θ_t is made based on $x_{j,t}(i,v)$ and θ_{t-1}. The individual prices are also affected by $z_{\ell,t}(i)$. As a result, the individual prices are a function of $x_{j,t}(i,v)$, θ_{t-1}, and $z_{\ell,t}(i)$. However, when we take the cross-sectional average of the individual prices, the noise in $x_{j,t}(i,v)$ is washed out and only θ_t remains in the aggregate prices. Similarly, we assume that the cross-sectional average of $z_{\ell,t}(i)$ across i is constant. Hence, suppressing the constant term, we can express the aggregate prices as (A1).

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

$$p_{j,t}(i,v) = (1-\alpha)\,\mathbb{E}_{j,t}(\theta_t|i,v) + \alpha c_0\mathbb{E}_{j,t}(\theta_t|i,v) + \alpha c_1\theta_{t-1} - z_t(i,v), \tag{A2}$$

from (11). Combining (11) - (13) for $j=1$ yields

$$\begin{aligned}
p_{1,t}(i) &= s(1-\alpha+\alpha c_0)\kappa_1\int_0^1 x_{1,t}(i,v)\,dv + (1-s)(1-\alpha+\alpha c_0)\kappa_1\int_1^2 x_{1,t}(i,v)\,dv \\
&\quad + [(1-\alpha+\alpha c_0)(1-\kappa_1)+\alpha c_1]\,\theta_{t-1} - sz_{1,t}(i) - (1-s)\,z_{2,t}(i) \\
&= (1-\alpha+\alpha c_0)\kappa_1\theta_t + [(1-\alpha+\alpha c_0)(1-\kappa_1)+\alpha c_1]\,\theta_{t-1} - sz_{1,t}(i) - (1-s)\,z_{2,t}(i) \\
&= (1-\alpha+\alpha c_0)\kappa_1\varepsilon_t^\theta + (1-\alpha+\alpha c_0+\alpha c_1)\,\theta_{t-1} - sz_{1,t}(i) - (1-s)\,z_{2,t}(i),
\end{aligned} \tag{A3}$$

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 $p_{2,t}(i)$:

$$p_{2,t}(i) = (1-\alpha+\alpha c_0)\kappa_2\varepsilon_t^\theta + (1-\alpha+\alpha c_0+\alpha c_1)\,\theta_{t-1} - sz_{2,t}(i) - (1-s)\,z_{1,t}(i). \tag{A4}$$

The definition of $q_t(i)$ implies

$$q_t(i) = (1-\alpha+\alpha c_0)\,\hat{\kappa}\varepsilon_t^\theta + (2s-1)\,z_t(i). \tag{A5}$$

The remaining task is to solve for c_0 in (A5). To find c_0, we take the log-linearization of

$P_t(i) = \left[(1/2)\sum_{j=1}^{2} P_{j,t}(i)^{1-\xi}\right]^{1/(1-\xi)}$ and $P_t = \left[\int_0^1 P_t(i)^{1-\xi}\right]^{1/(1-\xi)}$. The log-aggregate prices of good i across two cities are

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

Taking the integral of this equation across goods yields

$$p_t = (1-\alpha+\alpha c_0)\,\bar{\kappa}\theta_t + \left[(1-\alpha+\alpha c_0)(1-\bar{\kappa}) + \alpha c_1\right]\theta_{t-1}, \tag{A6}$$

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

$$c_0 = \frac{(1-\alpha)\,\bar{\kappa}}{1-\alpha\bar{\kappa}} \tag{A7}$$

Finally, arranging terms in the coefficient on ε_t^{θ} in (A5) yields (15).

A.2 Derivation of (16) - (18)

Equation (17) follows directly from the variance formula applied to (15). Let $\Gamma_q(i)$ and $\Gamma_z(i)$ be the first-order autocovariance of $q_t(i)$ and $z_t(i)$, respectively. From the definition of the first-order autocorrelation, we obtain (18):

$$\begin{aligned}\rho_q(i) &= \frac{\Gamma_q(i)}{var[q_t(i)]} = \frac{(2s-1)^2\,\Gamma_z(i)}{\phi^2\sigma_\theta^2 + (2s-1)^2\,var[z_t(i)]} \\ &= \frac{(2s-1)^2\,var[z_t(i)]}{\phi^2\sigma_\theta^2 + (2s-1)^2\,var[z_t(i)]}\rho_z(i),\end{aligned}$$

where the last equality comes from the definition of $\rho_z(i) = \Gamma_z(i)/var[z_t(i)]$. Also, because (8) implies that $z_{\ell,t}(i)$ for $\ell = 1, 2$ are uncorrelated, $var[z_t(i)]$ is

$$var[z_t(i)] = var[z_{1,t}(i)] + var[z_{2,t}(i)]. \tag{A8}$$

Also, the first-order autocovariance is

$$\begin{aligned}\Gamma_z(i) &= \Gamma_{z,1}(i) + \Gamma_{z,2}(i) \\ &= var[z_{1,t}(i)]\,\rho_{z,1}(i) + var[z_{2,t}(i)]\,\rho_{z,2}(i).\end{aligned} \tag{A9}$$

Taking the ratio of (A9) to (A8) yields (16).

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Table 1: Summary statistics

	Persistence measure			Volatility measure	
	ρ_q	SAR	Largest AR root	sd_q	$mapd_q$
All	0.520	0.534	0.542	0.136	0.158
	(0.151)	(0.149)	(0.147)	(0.038)	(0.045)
(Obs. = 63,648)	[0.238]	[0.244]	[0.246]	[0.057]	[0.089]
Less than 100 miles	0.482	0.493	0.503	0.127	0.127
	(0.174)	(0.173)	(0.166)	(0.040)	(0.046)
(Obs. = 624)	[0.250]	[0.254]	[0.250]	[0.056]	[0.076]
More than 2,000 miles	0.563	0.578	0.585	0.150	0.243
	(0.145)	(0.147)	(0.147)	(0.045)	(0.108)
(Obs. = 3,648)	[0.222]	[0.229]	[0.233]	[0.061]	[0.149]

NOTES: Reported numbers are the averages of the estimated persistence and volatility measures over goods and services where the total number of observations is denoted by "Obs." The LOP deviations, $q_{j,k,t}(i)$, are calculated as the logarithm of the relative price of a good or service in a city to the same good or service in a different city. The sample period is over 1990:Q1 - 2007:Q4. Persistence measures are the first-order autocorrelations (ρ_q), the sum of autoregressive coefficients (SAR), and the largest autoregressive root (Largest AR root). The AR order is selected based on the BIC. Volatility measures are the standard deviation (sd_q) and mean absolute price difference ($mapd_q$). The numbers in parentheses are the between-group standard deviations across 48 goods and services. The numbers in brackets are the total standard deviations. The upper panel shows statistics for all observations. The middle and lower panels show statistics among city pairs with distance being less than 100 miles and with distance being more than 2,000 miles, respectively.

Table 2: Persistence-distance regressions

Dependent variables	ρ_q				SAR				Largest AR root			
Regressors	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
$\ln dist_{j,k}$	0.020	0.020	0.019	0.019	0.023	0.023	0.022	0.022	0.026	0.026	0.025	0.025
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.002)	(0.002)	(0.002)	(0.002)
$distribution\ share_i$		0.342		0.280		0.322		0.259		0.261		0.202
		(0.004)		(0.005)		(0.004)		(0.005)		(0.005)		(0.005)
λ_i			0.209	0.129			0.214	0.140			0.213	0.156
			(0.004)	(0.004)			(0.004)	(0.004)			(0.004)	(0.004)
Good dummies	yes	no	no	no	yes	no	no	no	yes	no	no	no
Obs.	63,648	63,648	58,344	58,344	63,648	63,648	58,344	58,344	63,648	63,648	58,344	58,344
Adj. R^2	0.40	0.12	0.05	0.11	0.37	0.10	0.05	0.10	0.37	0.10	0.05	0.10

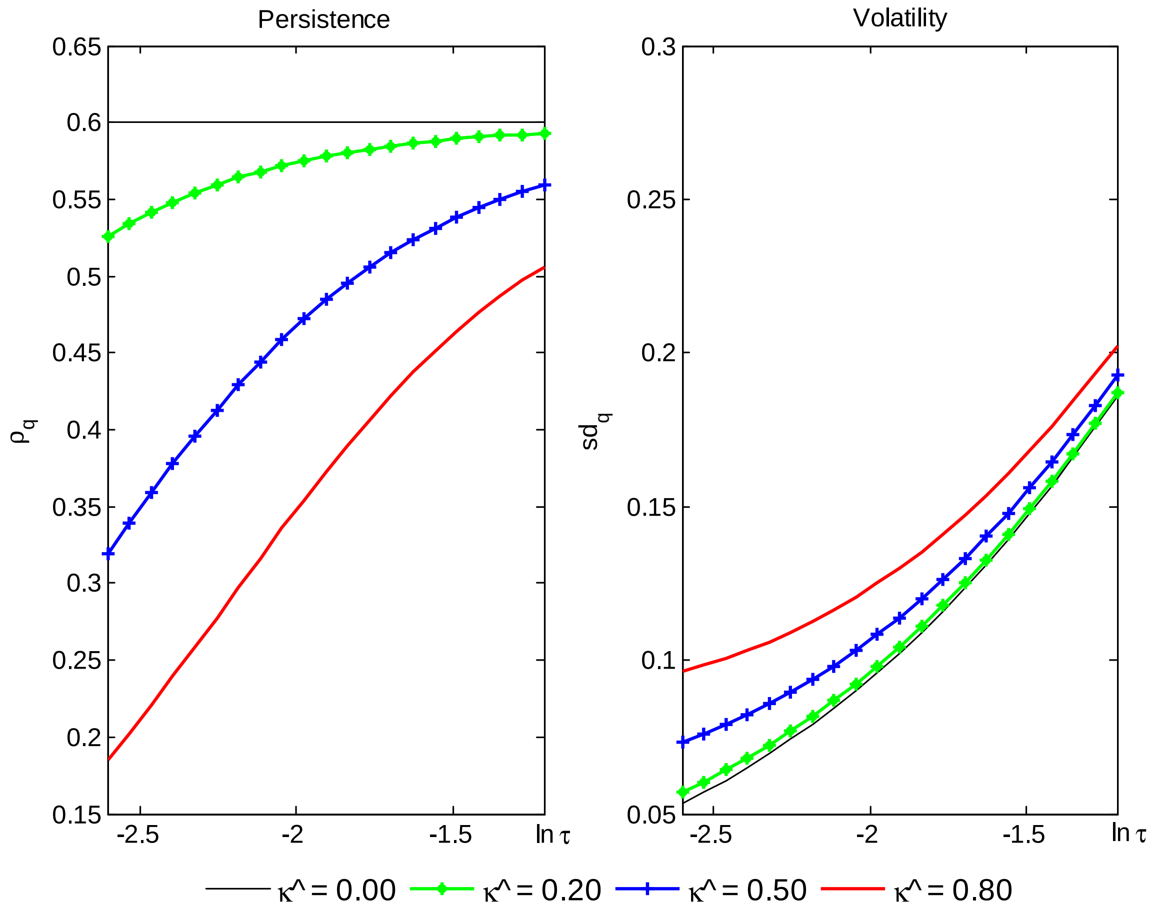
NOTES: The regressions are estimated using data for 48 items and 1,326 city-pairs. Standard errors clustered by city-pairs are given in parentheses below the coefficients. The regression coefficients are reported for distance ($\ln dist_{j,k}$), the distribution shares ($distribution\ share_i$) and the degree of price stickiness (λ_i). See the footnote of Table 1 for the detail of dependent variables. The number of observations (*Obs.*) in regressions are 63,648 for all items, and 58,344 if λ_i is used as a regressor, because no data of the degree of price stickiness is available for four items related to shelters (i.e., monthly rent for apartment, total home purchase price, mortgage rate, and monthly payment for house). The "Adj. R^2" in the last row denotes the adjusted R-squared.

Table 3: Calibrated regression slope in persistence-distance regressions

	$\hat{\kappa}$										$\hat{\kappa}$ consistent with data		
	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90	1.00	LB	UB	Range
A: The flexible price model													
$\alpha = 0.90$, $\rho_z(i) = 0.60$	0.000	0.000	0.001	0.001	0.001	0.002	0.003	0.004	0.005	0.006	-	-	-
$\alpha = 0.45$, $\rho_z(i) = 0.60$	0.001	0.003	0.008	0.013	0.019	0.026	0.033	0.041	0.048	0.054	0.449	0.570	0.121
$\alpha = 0.00$, $\rho_z(i) = 0.60$	0.002	0.007	0.014	0.024	0.034	0.044	0.053	0.061	0.067	0.072	0.319	0.405	0.086
$\alpha = 0.00$, $\rho_z(i) = 0.30$	0.001	0.003	0.007	0.012	0.017	0.022	0.027	0.030	0.034	0.036	0.483	0.648	0.165
$\alpha = 0.00$, $\rho_z(i) = 0.90$	0.003	0.010	0.022	0.036	0.051	0.066	0.080	0.091	0.101	0.108	0.255	0.320	0.065
B: The sticky price model ($\alpha = 0.00$, $\rho_z(i) = 0.60$)													
$\lambda(i) = 0.35$	0.001	0.005	0.010	0.017	0.024	0.031	0.038	0.043	0.048	0.052	0.392	0.506	0.114
$\lambda(i) = 0.65$	0.001	0.004	0.008	0.012	0.017	0.021	0.025	0.028	0.030	0.032	0.479	0.669	0.190
$\lambda(i) = 0.95$	0.001	0.004	0.005	0.005	0.004	0.004	0.003	0.003	0.002	0.002	-	-	-
C: The three-city, flexible price model ($\alpha = 0.00$, $\rho_z(i) = 0.60$)													
$(\tau_{1,2}, \tau_{1,3}, \tau_{2,3}) = (0.2, 0.2, 0.2)$	0.005	0.016	0.032	0.047	0.060	0.068	0.073	0.074	0.073	0.070	0.197	0.251	0.054
$(\tau_{1,2}, \tau_{1,3}, \tau_{2,3}) = (0.2, 0.3, 0.1)$	0.003	0.012	0.024	0.037	0.047	0.055	0.060	0.063	0.063	0.062	0.234	0.300	0.066
D: The three-city, sticky price model ($\alpha = 0.00$, $\rho_z(i) = 0.60$, $\lambda(i)$ =0.65)													
$(\tau_{1,2}, \tau_{1,3}, \tau_{2,3}) = (0.2, 0.2, 0.2)$	0.002	0.009	0.016	0.023	0.027	0.030	0.031	0.030	0.029	0.027	0.298	0.425	0.127
$(\tau_{1,2}, \tau_{1,3}, \tau_{2,3}) = (0.2, 0.3, 0.1)$	0.002	0.006	0.012	0.018	0.022	0.025	0.026	0.026	0.025	0.024	0.365	0.570	0.205

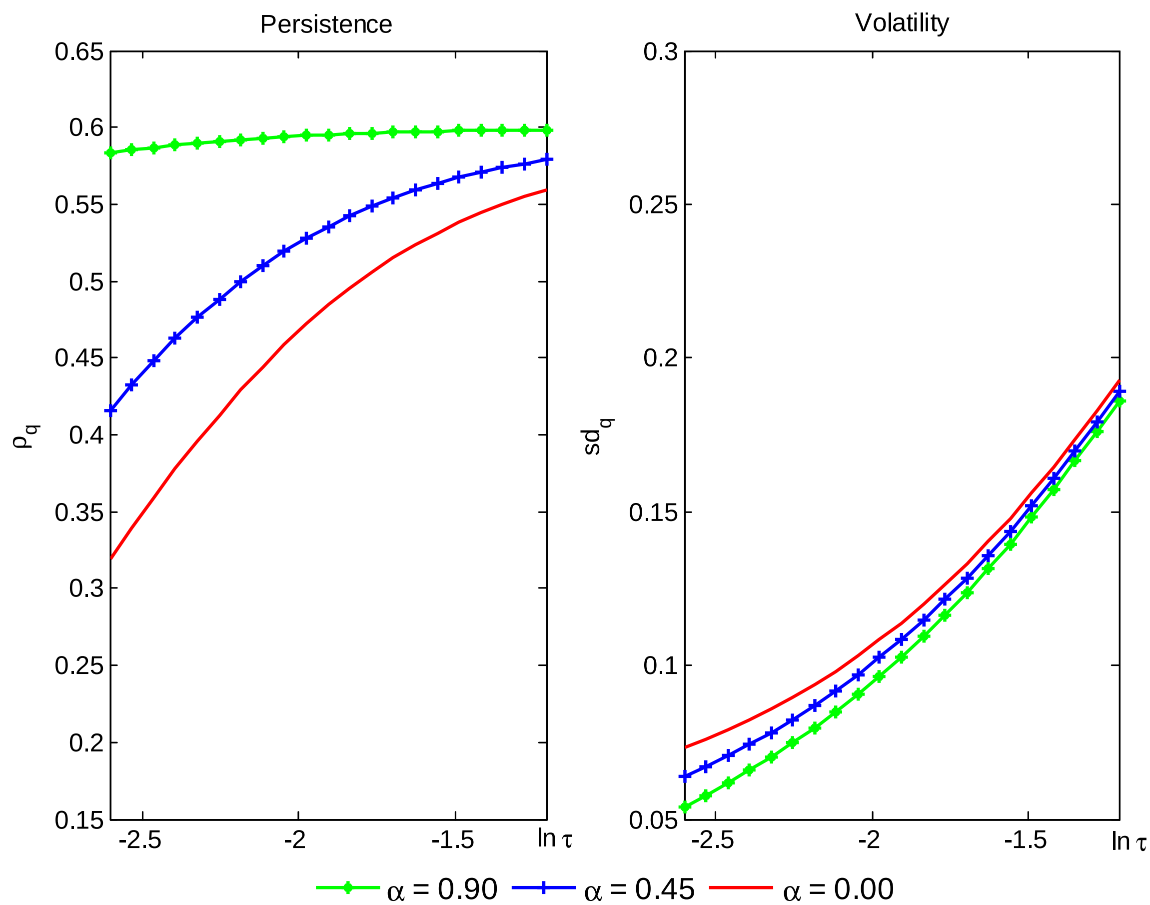
NOTES: Each number in the table represents the coefficients for the log-distance in persistence-distance regressions predicted by the noisy information model. The coefficients are obtained from the linear approximation of the theoretical first-order autocorrelation of $q_t(i)$ or $q_{2,1,t}(i) = p_{2,t}(i) - p_{1,t}(i)$ around $\bar{\tau} = 0.2$, along with the parameter values described in the main text. Lower bound (LB), upper bound (UB), and the range of $\hat{\kappa}$ consistent with the 95% confidence interval of regression slope in Table 1 are also shown. Panel A shows the baseline two-city flexible price model. Panel B shows two-city model with price stickiness. Panels C and D are the three-city models with and without sticky prices. In the first rows of Panels C and D, all trade costs are assumed to be the same across all three city pairs. The second rows of Panels C and D show the case when trade costs between cities 1 and 2 differ from the trade cost between other city pairs.

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



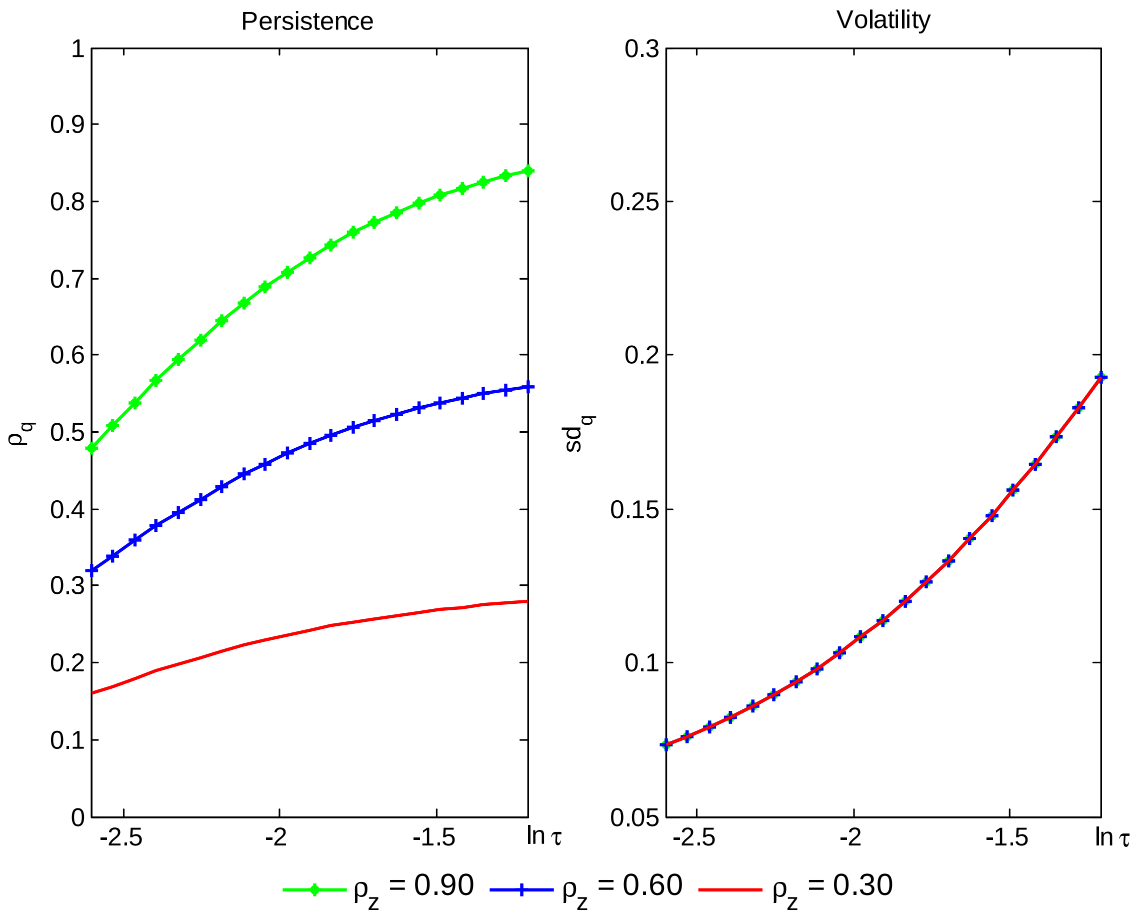
NOTES: Each line in the figure represents the first-order autocorrelation (the left panel) and the standard deviation (the right panel) of $q_t(i)$ against $\ln \tau$ for different values of $\hat{\kappa}$. For parameterization except for $\hat{\kappa}$, we use $\alpha = 0$, $\rho_z(i) = 0.6$, $\bar{\kappa} = 0.5$, $\xi = 4$, $\sqrt{var[z_t(i)]/\sigma_\theta^2} = 5$, $\bar{\tau} = 0.2$, and $\delta = 0.3$.

Figure 2: Effect of strategic complementarities α on persistence and volatility of LOP deviations



NOTES: Each line in the figure represents the first-order autocorrelation (the left panel) and the standard deviation (the right panel) of $q_t(i)$ against $\ln \tau$ for different values of α. For parameterization except for α, we use $\hat{\kappa} = 0.5$, $\rho_z(i) = 0.6$, $\bar{\kappa} = 0.5$, $\xi = 4$, $\sqrt{var[z_t(i)]/\sigma_\theta^2} = 5$, $\bar{\tau} = 0.2$, and $\delta = 0.3$.

Figure 3: Effect of the productivity persistence $\rho_z(i)$ on persistence and volatility of LOP deviations



NOTES: Each line in the figure represents the first-order autocorrelation (the left panel) and the standard deviation (the right panel) of $q_t(i)$ against $\ln \tau$ for different values of $\rho_z(i)$. For parameterization except for $\rho_z(i)$, we use $\hat{\kappa} = 0.5$, $\alpha = 0$, $\bar{\kappa} = 0.5$, $\xi = 4$, $\sqrt{var[z_t(i)]/\sigma_\theta^2} = 5$, $\bar{\tau} = 0.2$, and $\delta = 0.3$.