The Law of One Price: New Evidence from China (1997-2012)

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Abstract

This paper investigates the rate of price convergence across Chinese cities, and examines how international openness affect intranational price dispersion. Our panel cointegration methodology account for heterogeneity, cross-sectional dependence and seasonality. Using monthly prices of 267 goods from 172 cities in 1997-2012, our results suggest that prices converge for a majority of goods, and the convergence rate becomes faster since China entered into WTO. Using city-pair panel data, we identify that larger openness is associated with less price dispersion. Combining with tariff data, we have two main findings: 1) tariff reduction is only negatively associated with price dispersion for consumer goods but positively for industrial materials; 2) tariff reduction decrease the convergence rate for most of the goods. These results confirm that the China's openness promotes the domestic market integration but only for consumer goods in the short run. This pattern implies that China's domestic market integration is still incomplete.

Keywords: Law of One Price; Panel Cointegration; Micro Data
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Highlights

- The Law of One Price holds for an overwhelming majority of goods in China in the 1997-2012 period.
- China's price convergence has been over-estimated in the past studies.
- The rate of price convergence slowed down after China’s accession to the WTO in 2001.

I. Introduction

Although China has experienced prolonged economic growth and is highly integrated within the global economy since its economic reform of 1978, it has been argued that China's gradual reform has potentially led to a more fragmented internal market. Young (2000) and Lau *et al.* (2000) debate whether the liberalization of domestic market has led to the removal of interregional trade barriers, and whether China's gradualist reform has successfully established a market-oriented economy. The extent of inter-regional price movements is an important index to discuss whether considerable trade barriers exist in China. This research sheds light on this argument with new empirical evidence regarding the extent of China's market integration.

There is a large body of literatures which studies the market integration based on the estimated speed of price convergence. According to the law of one price (LOP), prices across fragmented markets need not converge to one another. As a result, the rate of price convergence is much slower under fragmented market. The rate of price convergence is frequently summarized by the half-life, the time needed for half the effect of a given shock to dissipate. There has been a surge of economic research about the LOP in China (Fan & Wei, 2006; Gui *et al.*, 2006; Chen *et al.*, 2007; Lan & Sylwester, 2010; Lu & Chen, 2009; Yu *et al.*, 2013) and other economies (Bernhofen *et al.*, 2015; Crucini & Shintani, 2008; Engel and Rogers, 1996; Parsley and Wei, 1996, 2001). Evidence on the law of one price in China is encouraging, as all the results indicate that China's market is well integrated. The half-life reported in Fan & Wei (2006) and Lan & Sylwester (2010) is even shorter than rates estimated developed countries in the other studies.

In contrast, the conventional wisdom is that China's domestic market was fragmented by provincial and administrative borders due to the decentralization and intra-national protectionism (Eberhardt *et al.*, 2015; Poncet, 2001, 2003 and 2005). Under the hierarchical politico-economic structure, intensive political competition provides incentives for local government to intervene and protect local manufacturing. Empirically, China's "border effects" have been identified and discussed in many studies about contemporary China (Huang *et al.*, 2013; Huang *et al.*, 2014).

Although Fan & Wei (2006) provide novel evidence covering the period 1990-2003 to confute Young (2000)'s remark of China's market fragmentation in the 1990's, their findings may not apply to China's economic performance in the 21st century. Since WTO accession in 2001, China has witnessed much faster economic growth and greater liberalization of international trade and investment. As the door to international trade opens, tariff protection has been reduced substantially, while a series of reforms have been carried out in China's State Owned Enterprises (SOEs). Some studies argue that China's export boom is the consequence of internal market fragmentation (Poncet 2001, 2003 and 2005; Zhu *et al.*, 2005). This is particularly interesting when identifying how market integration responds to these external shocks. However, little literature exists which systematically documents China's market integration after 2001. Yu *et al.* (2013) report and verify the substantial price dispersion in China's car market from 2004 to 2006, while we document (see Section3.2) that China's price dispersion has increased after 2001. Due to the lack of empirical evidence, it is not clear whether China's market remains highly integrated after 2001. In this study, the data coverage allows us to characterize the dynamic changes in market integration in China for the period 1997-2012.

This paper revisits the question regarding the degree of market integration with a long panel of commodity price data. Imbs *et al.* (2005) show that failure to allow for heterogeneity in the panels of disaggregated relative prices induces a bias in persistence estimates. We correct for dynamic heterogeneity using the Mean Group (MG) model introduced in Pesaran and Smith (1995). In addition, failure to address the network aspect of price movements including multilateral resistance and common shocks (i.e. cross-sectional dependence) can result in misleading inference and inconsistent estimators (Phillips and Sul, 2007; Sarafidis & Wansbeek, 2012). To capture cross-sectional dependence, our empirical investigation builds on the Pesaran (2006) common correlated effects (CCE) estimator to investigate heterogeneous price convergence at the provincial or national average.

Our empirical results show that an overwhelming majority of goods statistically converge toward the law of one price in China's market. Across all categories, perishable consumer goods are the most integrated. Accounting for heterogeneity, common correlated effects and seasonality, we find that China's convergence to the LOP occurs at a slower speed than that estimated by previous literature. However, the average half-life of deviations from the LOP estimated in this study (i.e. 9.34 month) is still shorter than the rate in OECD (19 month) and U.S. (18 month) estimated by Crucini & Shintani (2008). Moreover, through the dynamic comparison, we do find China's convergence speed was decreasing after entering WTO in 2001. On the one hand, our study provides empirical support that the LOP holds in China, which implies that the impact of local-government intervention and protectionism has been over estimated. On the other hand, the decreasing rate of convergence we identify implies that China's rapid economic growth is not necessarily associated with rapid price convergence.

This paper is organized as follows. Section II provides a brief literature review on the law of one price. Section III introduces the data used in this paper. Section VI introduces the methodology employed. Section V discusses the main empirical findings. The paper concludes in Section VI.

II. A Brief Literature Review

Since China's economic reform in 1978, its economy has gradually transitioned from a planned economy to a market-oriented economy. The intense debate about China's internal market integration was initiated by Young (2000), which argues that China's gradual reform (i.e. the dual-track system) has encompassed local-official rent-seeking behavior through local industry protection, and this lead to the market fragmentation. An insightful response from Lau *et al.* (2000) claims that local officials have the incentive to remove trade barriers since they will gain larger rents (e.g. larger market price) from the inter-regional trade. Since both sides provide convincing theoretical arguments, empirical evidence is necessary to resolve the ambiguity behind China's market evolution.

Despite the development of China's domestic market, provincial "border" effects and internal market fragmentation has received increasing attention in the trade literature. One stream of literature focuses on trade flows. Poncet (2001, 2003 and 2005) finds that Chinese provinces' larger involvement in international trade is associated with a decrease in inter-province trade flows. Zhu *et al.* (2005) argue that China's rapid export growth is the product of market fragmentation because the internal trade costs are higher than international trade costs. The other stream of literature focuses on the output and local protection. For example, Xu (2002) uses an error-components model to decompose provincial sectoral real value-added growth, and identifies that economic integration among provinces has progressed but is not complete. Eberhardt *et al.,* (2015) demonstrate how provincial governments use drug advertising inspection to impose local protectionism.

According to the law of one price, the prices for homogeneous products sold in different markets should converge to a stable differential (representing trade costs) due to arbitrage in the market. A fast growing literature about market integration uses price data to examine the extent of price co-movement across regions (Engel and Rogers, 1996; Parsley and Wei, 1996, 2001). For example, Engel and Rogers (1996) use CPI data for a set of US and Canadian cities to examine the deviations from the LOP. Some studies use China's yearly and provincial multiproduct price indices to compute price volatility across regions as a measure of market integration (Gui *et al.*, 2006; Chen *et al.*, 2007; Lu & Chen, 2009). Their results indicate that price dispersion in China decreased over the 1985-2001.

There are some problems, however, with using price indices instead of prices. First, the price indices are aggregated at the sectoral level and reported annually and, as such, are likely to be subject to aggregation bias (Elberg, 2016; Imbs *et al.*, 2005; Taylor, 2001). Second, China's price index measures the percentage change in prices in one location in period t relative to period $t-1$, which is lack of comparability across locations and produce estimation bias of market integration[1]. In Figure 1, we use monthly disaggregated data (Section III.2) for the period from 1997 to 2012 to show that China's price dispersion fell during the 1997 to 2001 period but then begun to increase from 2001 to 2012. How can we explain the rise in price dispersion after 2001 if most of the literature suggests that China's internal market is well integrated? This research will fill this gap with more disaggregated price data.

A new wave of research, fueled by newly developed econometric methods, uses panel unit root tests to investigate the patterns of intra-national price convergence. Parsley and Wei (1996) estimate the convergence rate using a panel of 51 commodities from 48 cities in the US, and they find that intra-national convergence rates are substantially higher than cross-country data. Rogers (2001) finds evidence of price convergence toward the LOP across countries in the euro zone in the 1990s. Goldberg and Verboven (2005) find strong evidence of car price convergence in Europe. Crucini and Shintani (2008) estimate the convergence rate using both a US and an international sample of prices across cities, and they find that the convergence speed within the US is faster. Using price of 40 products across 11 urban centers, Elberg (2016) finds evidence of remarkable convergence to the LOP in Mexico over the 2001-2011period. Fan and Wei (2006) investigates price convergence in China with data of 93 commodities in 36 major cities for 1990-2003. Lan and Sylwester (2010) estimate China's price convergence rate using 44 products from 36 cities from 1990 to 2004. Their results suggest that China's rate of price convergence is faster than other developed countries.

A simple pooled price convergence regression model imposes the assumption that all cities converge to the same long-run equilibrium price level. An example of this approach is the investigation of LOP in the European car market in Goldberg and Verboven (2005) using a pooled panel unit root test from Levin and Lin (1992).

[1] For example, in period t the food price index of city i and j is 120, which means 20% increase in both cities' food price relative to last period. However, the real average food price in city i is 50 yuan while the price in city j is 20 yuan. In this example, price indexes are the same but the real prices differ substantially such that price indexes are not sufficient to capture the real price difference between city i and j, which will definitely produce bias for estimating the speed of price convergence.

However, in reality differences in prices are sustained by limits to arbitrage which vary across cities and goods. Bernhofen *et al.* (2015) argue that there were heterogeneous rates of grain price convergence across prefectures during China's Qing Dynasty. Bils and Klenow (2004) find the price adjustment rate differs substantially across 350 goods in U.S. Here we argue that homogeneity in the convergence rate of each good across cities is a strong assumption. Imbs *et al.* (2005) show and explain how the failure to account for heterogeneity in relative price dynamics gives rise to positive bias in mean reversion estimates. Mean group (MG) estimation generalized in Pesaran and Smith (1995) is used to deal with heterogeneous dynamics in panel data, especially for long panel data where fixed effects are not sufficient to account for heterogeneity.

The second problem with the pooled convergence model is that it fails to address contemporaneous correlation across shocks to relative prices from different cities. The network aspect of price movements, including multilateral resistance and common shocks (i.e. cross-sectional dependence), can result in misleading inference and inconsistent estimators (Phillips and Sul, 2007; Sarafidis & Wansbeek, 2012).[2] To allow for cross-sectional correlation in the residuals, it is standard to implement Seemingly Unrelated Regressions (SURE-GLS) to correct the error terms (e.g. Elberg, 2016). An alternative methodology is the common correlated effects (CCE) estimator introduced in Pesaran (2006), which is well-tailored for large panels with both cross-sectional independence and heterogeneity. Pesaran (2006)'s estimator provides a correction to the MG estimator that accounts for unobserved common factors potentially correlated with individual-specific regressors.

SURE requires that the cross-sectional dimension (*N*) be smaller than the time dimension of data (*T*), which, unfortunately, is not the case in our data. Although our data cover 290 goods across 170 cities over the 1997-2012 period, the prices of some goods are only available for a short period such that their *T* dimension is much shorter. In CCE, all cross sections can be included, which keep identification parsimonious and may yield more accurate estimates than SURE (Imbs *et al.*, 2005). In this study, our empirical methodology mainly follows the MG-CCE model generalized in Pesaran (2006).

III. Data

III.1 Data

[2] O'Connell (1998) shows that failure to account for cross-section correlation may lead to severe size distortions in the unit root tests.

The data set used in this empirical study is a panel data set of monthly prices collected by the China Price Information Center (CPIC) and used as the basic source for official CPI construction. In the raw data, each commodity is narrowly defined (e.g., "Stainless steel plate, 1.0, 304/2B, cold rolled") and has been labeled clearly by grade, price type and unit. As a result, the comparability of the same commodity across cities can be guaranteed. The price of each commodity is collected from several designated markets within one city with different frequencies. For example, energy prices are collected monthly while perishable consumer goods prices are collected every 10 days. The data collection process is performed by CPIC's own personnel who visit stores or supermarkets with the required frequency. In this study, to maintain the comparability of prices across goods, we transform the raw data to a monthly panel of price data. As a result, the aggregated mean price of commodity i in city j from several designated markets in each month is i's monthly market price in city j. In this study, our monthly data are divided into groups of energy products, non-perishable consumer goods, perishable consumer goods, agricultural goods, processed industrial goods, raw industrial goods, and services. [3]

This data has a fair amount of missing information, especially for the early period. To guarantee the comparability of prices across categories, we choose the period between 1997-2012. To avoid the small-sample problem, we excluded any city for which there were fewer than 100 observations and any city-product pair has fewer than 36 observations. The basket of commodities varies each year. To guarantee comparability across years, we excluded the commodities which appear in less than two years. In Table 1, after these exclusions, our data set remains unbalanced, and both the geographical coverage and the number of products varies across categories. Because of the great coverage, the panel data we use is more nationally representative than the previous literature. Our data set comes from the same source for the data in Young (2000), Fan and Wei (2006) and Lan and Sylwester (2010) but has a much larger sample size, which strongly supports that our results are comparable with the previous empirical findings about LOP in China.

Table 1
Price Data Coverage

	(1)	(2)	(3)	(4)	(5)	(6)	(7)

[3] Table A.1 in Appendix A presents description of sample products used in this study.

	Energy	Non-perishable	Perishable	Agricultural	Processed industrial	Raw industrial	Services
Obs.	73569	326711	780592	108266	493035	338649	115779
City No.	61	154	160	147	160	156	145
Goods No.	58	28	47	25	88	32	12
Period	***2001-2012***	***1997-2012***	***1989-2012***	***1997-2012***	***1989-2012***	***1989-2012***	***1997-2012***

The reliability and quality of this data set has been discussed intensively in Fan and Wei (2006). CPIC is a division of China's State Planning Committee, which is responsible for collecting, analyzing and monitoring disaggregated price change. Since this data is the basic resource for CPI construction and highly correlated with the cost of living, the government and CPIC have strong incentive to maintain the quality of this data. Second, all of the prices in this data are spot prices regularly collected from various large department stores or supermarkets across different cities. Even though local officials in each city or province have an incentive for price manipulation, an individual official is unlikely to be able to systematically manipulate the whole data set. Instead of annual price indices, monthly variations in market prices correspond well to the time needed for price adjustment under arbitrage, which reduces the bias arising from temporal aggregation introduced in Taylor (2001).

Following the propositions in Young (2000) and Fan and Wei (2006), the above categorization accounts for several key determinants of price convergence. First, production of industrial materials (i.e. raw and processed industrial materials) still face regulation by the central government, and are subject to a large degree of control under the local monopolies. As a result, we expect to observe a lower degree of price convergence in industrial materials markets. Second, the market of non-perishable goods is more likely to be subject to imperfect competition while the market of perishable goods is better characterized by prefect competition. Third, non-perishable goods were more profitable than perishable goods, and thus were more likely to be prone to local protection and price discrimination. Therefore, we should observe that perishable goods were more integrated than non-perishable goods.

III.2.Basic Statistics Description

We now turn to the basic statistics of our data. Similar to Cecchetti et al. (2002), O'Connell and Wei (2002) and Fan and Wei (2006), we define relative price as

$$P_{i,j,t} = \ln p_{i,j,t} - \ln \overline{p}_{i,t}$$

, (1)

where $p_{i,j,t}$ denotes the raw price of product i in city j at time t; $\overline{p}_{i,t}$ denotes the mean of $p_{i,j,t}$ over cities as the national mean of product i at time t. Following the past literature, we have calculated the standard deviation (i.e. SD_t) of the relative price $P_{i,j,t}$ at each t to measure time varying national price dispersion (i.e. variability of price differentials at the national level). With respect to LOP, we assume that if trade costs are zero and there are no market fraction, product i has the same price in each city at time t such that

$$p_{i,1,t} = p_{i,2,t} = \ldots = \overline{p}_{i,t},$$

which suggests that both $P_{i,j,t}$ and SD_t are equal to zero. However, given impediments to arbitrage of goods and services, the price differential at any city and time may differ from zero. Intuitively, smaller values of SD_t imply smaller price dispersion and smaller deviations from LOP in at time t across all locations. Alternatively, we measure relative price deviations at the provincial level as

$$P^*_{i,j,t} = \ln p_{i,j,t} - \ln \overline{p}_{i,Q,t}, \qquad (2)$$

where $\overline{p}_{i,Q,t}$ denotes the mean of product i over cities in province Q at time t. The standard deviation of $P^*_{i,j,t}$ at each t (i.e. SD^*_t) measure how prices deviate from their provincial mean in each period.

Monthly measures of SD_t and SD^*_t are given together in Figure 1, which describe the trend of price dispersion over the 1997-2012 period. As expected, SD^*_t is lower than SD_t in each period, which shows that prices are closer to their provincial mean rather than the national mean. There are two possible explanations for this finding. First, each city is geographically closer to the other cities within the same province. Given that trade costs are proportional to the transport distance, inter-city trade within the same province suffer smaller trade costs. Second, the differential between SD_t and SD^*_t captures the border effect including political protectionism, cultural differentials and some other institutional factors which generate inter-province trade costs. From Figure 1, we can see that SD^*_t increases over the entire period while SD_t decreases from the beginning of 1997 until 2001 and then turns into an upward trend. Decreasing price dispersion before 2001 is consistent with the findings in the previous literature, which imply that China's market is well integrated. However, the conclusion based on the early stage cannot explain the increasing variability of price differentials to the national mean after 2001.

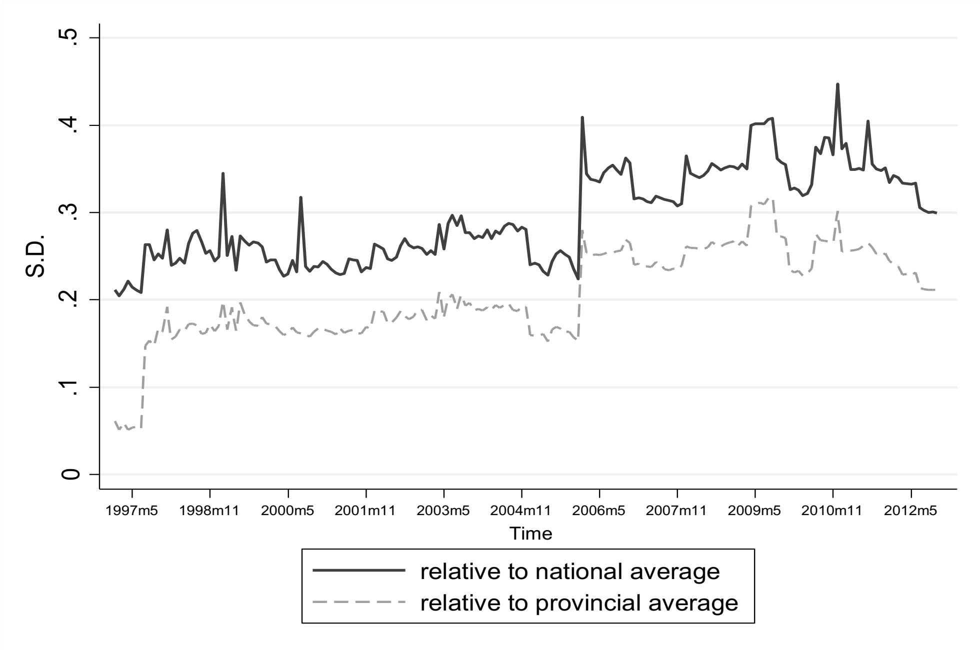

Fig.1 Variability of Price Differential (1997-2012)

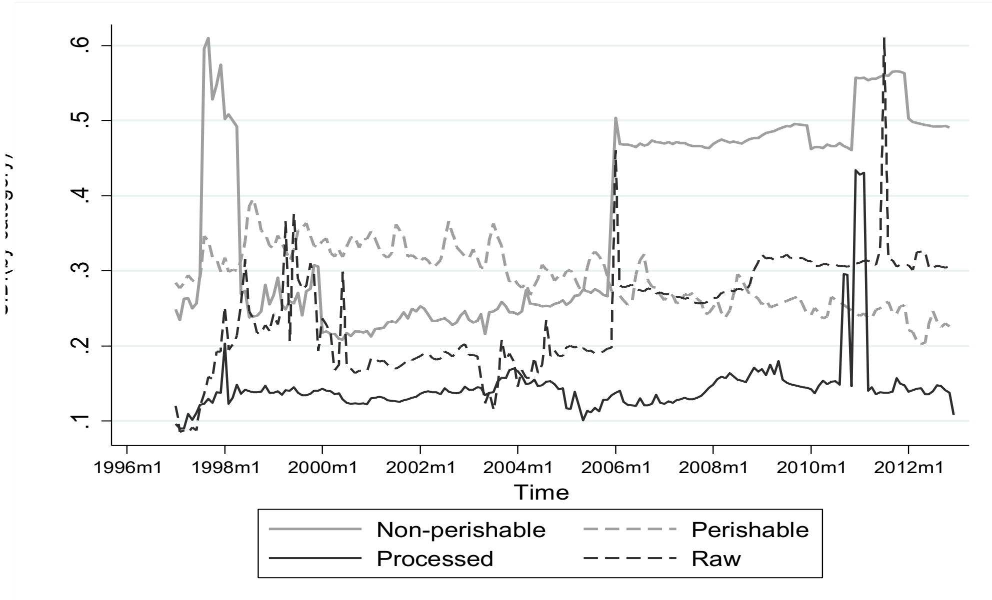

Fig.2 Variability of Price Differential (by category, 1997-2012)

In Figure 2, we calculate and report the monthly standard deviation of $P_{i,j,t}$ by category. For ease of interpretation, we only provide the plots of the four categories we are most interested in: perishable goods, non-perishable goods, processed industrial materials and raw industrial materials. The price variability of perishable goods witnessed a stable decrease throughout the whole period while non-perishable goods experience an opposite trend after 2000. Among industrial materials, processed industrial materials remain stable while raw industrial materials witness larger price variability after 2005. The dynamic ordering of magnitudes for these four categories is not consistent with findings and discussion in Fan and Wei (2006). Before 2005, perishable goods have the largest variation, which follows from Fan and Wei (2006)'s explanation that perishable goods are more difficult to store and transport. However, after 2005, non-perishable goods have the highest degree of price variability while perishable goods experience a fall in the price variation. The different trends of perishable and non-perishable goods suggest that price variation in China was mainly affected by the degree of tradability and market structure.

III.3Unit Root Test

A common approach examining price convergence is to use the panel unit root test to examine whether series of differential prices are stationary. The rejection of the panel unit root hypothesis suggests that relative prices will converge in the long run. In the cointegration literature, it is regular to test the unit root of each individual time series before the cointegration test. If these individual time series are stationary, it is not sensible to discuss whether their differential is stationary or not. In general, the literature considers that panel unit root tests have larger power than single time series unit root test (e.g. ADF test) for pooled time series data. Before a formal empirical discussion, we use the panel unit root test developed by Maddala and Wu (1999) (MW test) to evaluate the non-stationarity both in the raw price $p_{i,j,t}$ and price differential $P_{i,j,t}$.

The MW test assumes that all series are non-stationary under the null hypothesis against the alternative that at least one series in the panel is stationary, which is based on the *p*-value of individual unit root tests. If the *p*-value under MW test is below 0.05, we reject the null hypothesis of the panel unit root at 5% significance. Table 2 gives the percentage of goods which reject the null hypothesis at 5% significance (i.e. *p*-value<=0.05) both in the price and the relative price by categories. In general, it shows that prices in 50% of goods have a unit root while the price differentials (i.e. $\ln p_{i,j,t} - \ln \overline{p}_{i,t}$) of 80% goods are stationary. For price differentials in column (2), nearly all categories have a very high ratio of goods rejecting the hypothesis of panel unit root, with the exception of the energy and service sectors. The results are very similar to those in Fan and Wei (2006) and suggest that prices converge to the cross-city mean for most goods. The results in Table 2 suggest that LOP holds in China. MW allows for heterogeneous convergence across sectors, but it is not valid under cross-correlated error terms. In the following sections, we account for unobserved common factors as well as heterogeneity to obtain more accurate estimates of price convergence. In column (1), although nearly 50% of goods seem to be stationary, our estimates from MG-CCE does not rely on certain time series properties (nonstationarity) as a condition for price convergence.

Table 2:
MW Panel Unit Root Test

MW test H_0: All series are non-stationary		
Product category	% of goods ($p<=0.05$)	
	(1)	(2)
	Price	Price differential
Perishable consumer goods	55	100
Nonperishable consumer goods	68	86
Raw industrial materials	75	97
Processed industrial materials	68	88
Agricultural goods	36	84
Energy	1.7	36
Services	0	67
Overall	48	79

IV. Methodology

The LOP implies that the prices of homogeneous commodities tend to converge to the same level across cities by arbitrage. In mathematical terms, studying price convergence is to test the stationarity of the price differentials. In the following we first describe the panel unit root test used to exmine price convergence, then discuss the method used to identify the impact of transportation costs and time trend on price dispersion.

IV.1 Mean-Group Estimator with Common Correlated Effects

Having found supportive evidence for price convergence with the first generation panel unit root test in Section III.3, we turn to estimating rate of the convergence with the second generation panel unit root test. The methodology here follows mean group (i.e MG) estimator in Pesaran (2006) and Bernhofen *et al.* (2015) for investigating heterogeneous price convergence with common correlated effects (MG-CCE). We focus on the half-life of a deviation from the LOP as a measurement of the persistence of shocks to the LOP. In contrast to existing literature, our estimator is robust but does not rely on certain time series properties of the data (nonstationarity) as the condition to test price convergence.

Following the panel unit root literature, we conceptualize the rate of convergence for commodity i by measuring how quickly prices of commodity i return to their equilibrium level. The long time series dimension of the data also allows us to examine the dynamic changes of price convergence. National price convergence for commodity i is then modeled by the following convergence equation:

$$\Delta P_{i,j,t} = \alpha_{i,j} + \beta_{i,j}^{LPN} P_{i,j,t-1} + \sum_{l=1}^{T_{i,j}} \delta_{i,l} \Delta P_{i,j,t-l} + \varepsilon_{i,j,t} \quad (3)$$

where the relative log price level is $P_{i,j,t}$ and is defined in (1). The dependent variable in the so-called 'Dickey-Fuller regression' equation (3) is the first difference of this relative log-price level where the sum on the right-hand side (i.e. $\sum_{l=1}^{T_j} \delta_{i,l} \Delta P_{i,j,t-l}$) represents lags of this difference included to capture short-run price behavior. If an individual price series of commodity i in location j converges to i's national average, then $\beta_{i,j}^{LPN}$ will be negative and significant. Under the null of no convergence, it is equal to zero. In (3), the constant term $\alpha_{i,j}$ captures city-level time-invariant heterogeneity in commodity i which will help explain price differentials across cities within China. The inclusion of the constant term also captures whether prices converge to absolute or relative price parity. The number of lags $T_{i,j}$ are determined by the Akaike Information Criterion (AIC) in the regression for city j of commodity i.

The above empirical equation yields a total of N heterogeneous convergence coefficients for commodity i and we follow the standard in the literature (Pesaran and Smith, 1995; Pesaran, 2006) and report the Mean Group estimate for this set of coefficients for commodity i:

$$\hat{\beta}_i^{MG} = (\Sigma w_{i,j} \hat{\beta}_{i,j}^{LPN}) / N_i \quad (4)$$

where $w_{i,j}$ represents a set of city-specific weights applied in the computation of the average to reduce the impact of outliers.[4]

Our empirical implementation thus far resembles a standard first generation panel unit root test such as the Maddala and Wu (1999) test which was used in previous studies of LOP (e.g. Fan and Wei, 2006). Significant progress in this econometric literature focuses on dealing with the bias arising from unobserved time-varying heterogeneity in the panel, commonly referred to as cross-sectional dependence (Bai and Ng, 2002; Pesaran, 2006). To capture the impact of these shocks, we use the model introduced in Pesaran (2006) to account for a common correlated

[4]In practice I employ robust regression models to estimate these weights (Hamilton, 1992).

effects (CCE) and correct the MG estimator in (4). The MG-CCE estimator is straightforward to implement since the common factor correction for the MG estimator simply amounts to including lagged cross-sectional means in the Dickey-Fuller regression performed by MG. In practice, we augment the city-level regression (3) and add national averages of the dependent and independent variables as below:

$$\Delta P_{i,j,t} = \alpha_{i,j} + \beta_{i,j}^{LPN,CCE} P_{i,j,t-1} + \sum_{l=1}^{T_{i,j}} \delta_{i,j,l} \Delta P_{i,j,t-l}$$
$$+ \lambda_{i,j}^{P1} \overline{P_{i,t-1}} + \sum_{l=0}^{T_{i,j}} \lambda_{i,j,l}^{P2+l} \overline{\Delta P_{i,t-l}^{T_{i,j}}} + \sum_{C=1}^{11} \gamma_{i,C} M_{i,C} + \varepsilon_{i,j,t} \quad (5)$$

Specifically, $\overline{P_{i,t-1}}$ and $\overline{\Delta P_{i,t-1}}$ are the national average of $P_{i,j,t-1}$ and $\Delta P_{i,j,t-1}$ respectively. We include centered seasonal dummies (i.e. $M_{i,C}$)[5] to capture the effect of heterogeneous seasonality across product *i*. After the CCE correction of product *i*'s convergence in each city *j*, the MG-CCE estimator of product *i* will be obtained from equation (6) which is the augmentation of equation (4). Equation (6) measures product *i*'s speed of convergence to its national average.

$$\hat{\beta}_i^{MG,CCE} = (\Sigma w_{i,j} \hat{\beta}_{i,j}^{LPN,CCE}) / N_i \quad (6)$$

The half-life is commonly used in the PPP and LOP literature and is defined as the number of periods it takes until half the effect of a shock has dissipated. It can be computed using the estimated rate of convergence. The half-life of national convergence rate is calculated as $\ln(0.5)/\ln(\hat{\beta}_i^{MG,CCE}+1)$. Because the time dimension of our data is long (monthly data for up to 16 years), instead of analyzing price convergence over the entire time horizon, we investigate a 7-year rolling window (a maximum of 84 monthly observations) for each commodity so as to capture any structural changes in the convergence process over time. Our main results are then presented in graphical form.

IV.2 Price Dispersion Determinants

Panel unit root tests allow us to examine whether prices converge or not. However, this method does not enable us to identify the determinants of price fluctuations over time. For this purpose, we use a specification that closely follows the methods in Parsely and Wei (2003) and Fan and Wei (2006).

We first define log price differential for commodity *i* between any city pair *j* and *k* at time *t* as

[5]The construction of centered (orthogonalized) seasonal dummy variables follows Juselius (2006), which shift the mean of price without contributing to the trend. I construct centred seasonal dummies for each month. For example, for January, $M_{c=1}$=(11/12) if C is equal to 1, otherwise, $M_{c=1}$=(-1/12).

$$Q_{i,jk,t}=\ln p_{i,j,t}-\ln p_{i,k,t} \tag{7}$$

Then, we define

$$q_{i,jk,t}=Q_{i,jk,t}-Q^*_{i,t} \tag{8}$$

where $Q^*_{i,t}$ is the mean of $Q_{i,jk,t}$ over all city pairs. Then $S_{jk,t}$ denotes the standard deviation of $q_{i,jk,t}$ across commodities at time t for city pair jk, which captures the price dispersion between cities j and k at time t. $S_{jk,t}$ is the dependent variable while the independent variables include:(1) the yearly trend T, (2) the log of distance (measured by the greater circle method) between two cities ln_Dis_{jk}, (3) a dummy Big_Cities_{jk} indicating if the two cities are among the 36 first-tier cities, (4) a dummy $Coastal_{jk}$ indicating that if two cities are all located in the coastal provinces of China, (5) fixed effects of city j, city k and the calendar months denoted as Π_j, Π_k, and Π_M :

$$\begin{aligned} S_{jk,t} &= \rho_0 + \rho_1 \ln\_Dis_{jk} + \rho_2 Big\_Cities_{jk} + \rho_3 Coastal_{jk} \\ &+ \rho_4 T + \prod\nolimits_j + \prod\nolimits_k + \prod\nolimits_M + \varepsilon_{jk,t} \end{aligned} \tag{9}$$

Regression (9) shows how price fluctuations change over time and how they are affected by distance and geographical location. It is expected that ρ_1 is positively significant since transportation costs are part of the trade costs that hinder the arbitrage. It is interesting to investigate whether more modern and open cities are associated with more integrated markets through ρ_2 and ρ_3. Fan and Wei (2006) expect that ρ_3 is significantly negative because these coastal-city markets developed earlier and faster, but they cannot find supportive evidence. In our study, the larger data set and greater geographical coverage enables us to construct a Big_Cities_{jk} variable along with a $Coastal_{jk}$ variable to further check Fan and Wei's hypothesis.

We run regression (9) with all commodities as well as separate regressions for each category. In the latter case, it is more straightforward to characterize the different pattern of price dispersion across categories. The ideal regression in this setting would be for each product in each city pair since price dispersion trend may be heterogeneous across products even for products in the same category. However, due to the large number of commodities investigated in this study, we run regressions simply by combining all commodities.[6] Since the commodities from the same category are more likely to follow the same pattern, the regression results for separate categories may suffer less from aggregation bias.

V. Results

This section examines the long-run convergence to LOP in China by comparing

[6] Fan and Wei (2006) face the same problem, and our number of commodities is much larger than theirs.

MG-CCE estimates over various periods. For interpretational convenience we mainly focus on price differentials relative to a benchmark price (i.e. national average price).

V.1 Mean-Group Estimator with Common Correlated Effects

We begin with our analysis of price convergence over the entire time horizon. Figure 3 provides the national convergence rate (i.e. $\hat{\beta}_i^{MG,CCE}$) for all the goods with the 95% confidence interval.[7] The hollow point means that this good does not converge significantly, and there are 20 out of 261 products (7.6%) which are insignificant at the 5% level. In Figure 3, national convergence estimates are presented by the order of the coefficients magnitude for national convergence such that the blue line (i.e. national convergence) increases smoothly with the coefficient rank. Larger absolute value for convergence speed implies faster convergence to the equilibrium after a shock. For most goods, it is evident that the prices converge to the long-run equilibrium (i.e. national mean). The right side of Figure 3 reports the half-life of each product, which shows that for the majority of goods the half-life is in the range between 1-20 months. These results suggest that the LOP holds in China in the given period, although the rate of convergence is considerably heterogeneous across products.

The average half-life of each category is given in column (5) of Table 3. The results show that the average half-life estimates for perishable consumer goods is the smallest (i.e. 4.1 months), while the one for non-perishable consumer goods is quite large (i.e. 13.83 months). Since most of the perishable goods are very similar across cities (i.e. cucumber), perishable goods better capture the theoretical assumption of product homogeneity in the Law of One Price and unsurprisingly provides the stronger evidence for price convergence. In contrast, market fragmentation among non-perishable goods is more serious. One explanation is that non-perishable goods are more likely to be subject to imperfect competition. This imperfect competition allow price-discrimination across cities to led price differential to be persistent (Simonovska, 2015). The average half-life estimate for raw (i.e. 9.54 months) and processed materials (i.e. 5.81 months) are both smaller than that of non-perishable goods. These observations contradict Young (2000)'s proposition that industrial materials are more prone to local protection since they are more profitable and a large portion of their production is under the control of local monopolies. Of all categories,

[7] We get missing value of estimator for 29 products, which is due to the large share of missing value for these products.

services experience the slowest price convergence which may be due to the lack of tradability in services.

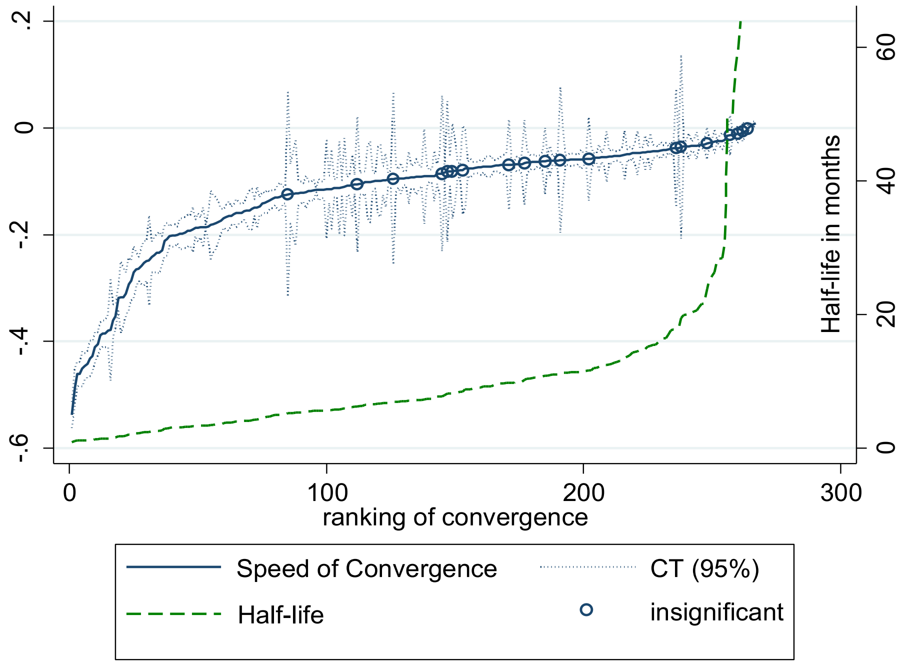

Fig.3 Price Convergence and Half-life (1997-2012)

At the bottom of column (5), we report that the average half-life across all products is 9.34 months, which is much slower than Fan and Wei (2006)'s estimator for China (i.e. 2.35 months) and Ceglowski (2003)'s estimator for Canada (i.e. 0.55 year) but still faster than Parsley and Wei (1996)'s estimator for the U.S. (i.e. 4-5 quarters). The first interesting finding is that China's markets are more integrated than those in the United States. One possible explanation is that Levin-Lin panel unit root test (i.e. one type of first generation panel unit root test) explored in Parsley and Wei (1996) requires homogeneous convergence speed for all products, which overestimates the half-life. However, other studies similarly report that developed countries markets are not necessarily more integrated than those in developing countries. Elberg (2016)'s average half-life estimate for Mexico is only 3 - 6 weeks while their methodology controls for for heterogeneous convergence across products as well as nonzero contemporaneous correlation between shocks. Using a GMM estimator for a dynamic panel model, Crucini and Shintani (2008) find that the average half-life across less developed countries (LDC) cities (i.e. 12 months) is faster than the estimate for the U.S. (i.e. 18 months) and OECD (i.e. 19 months). It is possible that the more restrictive price regulation implemented in the developing countries may make the prices move in a similar manner across cities.

It is also of interest to determine why our estimates differ substantially from the results in Fan and Wei (2006) even though both studies use the same data set (but cover a different set of products). In terms of methodology, in addition to the heterogeneity considered in Fan and Wei (2006), our estimates also account for CCE and seasonality as discussed in Section IV. From a direct comparison between column (1) and (5), while our data covers more cities and products, our convergence rate estimate (e.g. 9.34 month) are four times slower than that in Fan and Wei (e.g. 2.35 months). The largest difference between this study and Fan and Wei (2006) appears in the service sector, where our estimate (i.e. 33.74 months) is 11 times slower than that in Fan and Wei's (e.g. 2.44 months). It seems that our result is more convincing because the services are almost completely untradeable across cities in China. In columns (2) to (4), we restrict the sample to use the same period (i.e. 1990-2003) and city coverage (i.e. 36 first-tier cities) as in Fan and Wei's data, and relax the CCE in (2). However, our estimates are still much slower than those reported in Fan and Wei (2006).[8]

In columns (6) and (7), the average half-life increases slightly in each category in for latter period, where the agricultural sector experienced the largest increase in the rate of convergence. Through columns (2) to (7), perishable goods always have the fastest rate of convergence while non-perishable products' rate of convergence is much slower than raw and processed industrial materials. Service and energy also have relatively slow convergence, which may be due to the fact that these two sectors are still highly regulated by the central government. The results in Table 3 confirm that LOP holds in China, but they further suggest that the convergence speed to the LOP in China has been over-estimated in Fan and Wei (2006).

Table 3
Average Half-Life (Month) by Categories and Periods

	F & W (2006)	This study					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	1990-2003	1990-2003	1990-2003	1990-2003	1997-2012	1999-2006	2006-2012
No. Cities	36	36	36	160	173	171	135
No. Product	93	128	128	131	268	*266*	*245*
Seasonality	No	Yes	Yes	Yes	Yes	Yes	Yes
CCE	No	No	Yes	Yes	Yes	Yes	Yes
Product category	Half-Life	Half-Life	Half-Life	Half-Life	Half-Life	Half-Life	Half-Life

[8] In appendix 2, we compare the half-life of national convergence (1997-2012) for each product between, with, and without CCE. The results show that the exclusion of CCE will bias the estimator but the degree of bias is not large enough to explain the difference in results between this study and Fan and Wei (2006).

Perishable	1.66	3.52	3.54	3.4	4.1	3.8	3
Nonperishable	2.41	7.92	8.95	9.09	13.83	11.22	10.98
Raw industrial	2.59	6.08	5.84	8.01	9.54	8.39	7
Processed industrial	2.82	5.11	5.73	6.57	5.81	5.89	4.65
Agricultural		6.92	10.05	9.66	9.54	11.08	6.25
Energy					11.67		8.03
Services	2.44				33.74		11.55
Overall	2.35	5.42	6.08	6.57	9.34	7.06	7.19

V.2 Dynamic National Convergence

It is interesting to look at the dynamics of price convergence in China. To do so, we estimate the national convergence rate (i.e. $\hat{\beta}_i^{MG,CCE}$) with a moving window (i.e. each 7 years) for each product. To simplify the graph, Figure 4 shows the distributions of our estimates for all products in three periods (i.e. 1999-2006, 2003-2009, 2006-2012). Obviously, although the variance around the median changes slightly by period, the median convergence rates were almost the same. If we compare the distribution of 1999-2006 and 2006-2012 period directly, their shapes are very similar. Figure 5 shows the convergence rate by category in different periods, and the estimates are reported by the rank speed of convergence in each category for the 2003-2009 period. The largest degree of overlap appears among the perishable goods, which suggests that their convergence rates do not significantly vary over time. In raw and processed industrial materials, the convergence rates seem to increase after 2006, especially for the high ranking products, which is an encouraging finding with regard to market integration since the industrial materials market in China is more prone to local protection. On the other hand, for non-perishable consumer goods, there is no difference between the 1999-2006 and 2006-2012 periods.

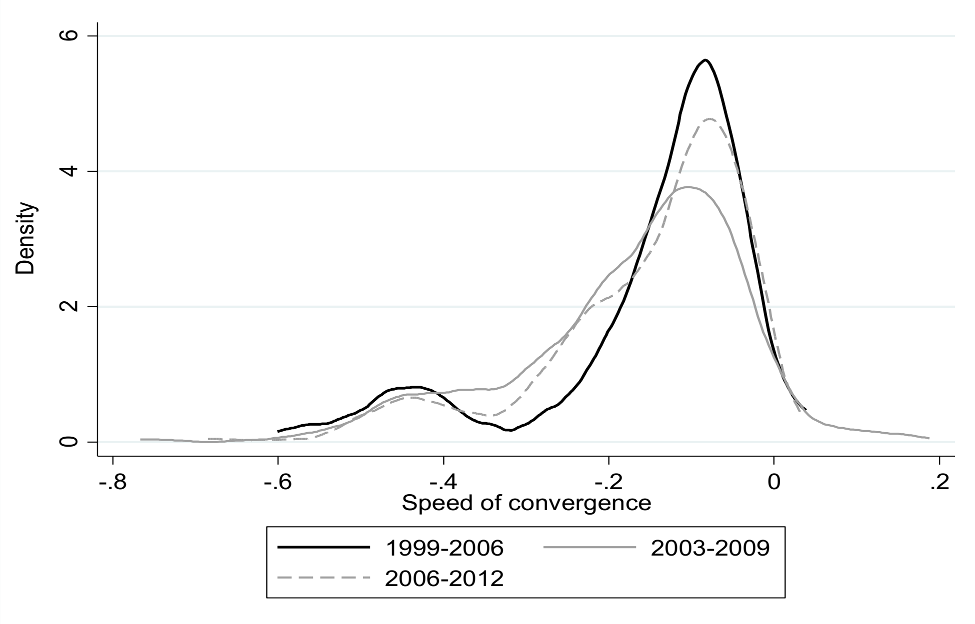

Fig.4 Empirical Distribution of Convergence Speed (kernel density)

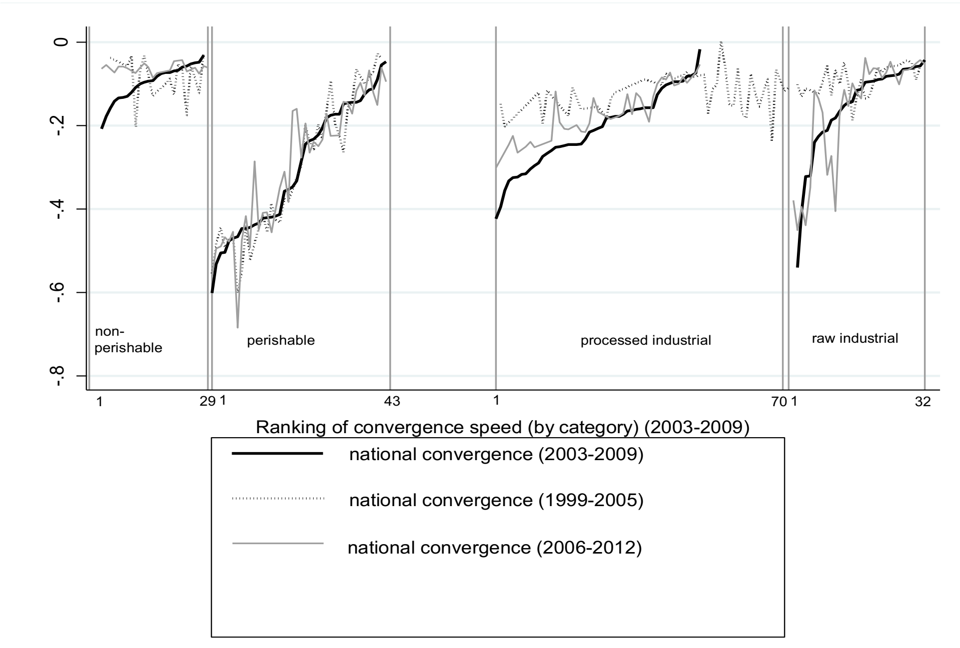

Fig.5 Dynamic Convergence by Category

In Figure 6, the moving mean (median) half-lives over each 7 years are reported where the x-axis represents the end year of moving window. There are two key observations in Figure 6. First, both the periodical mean and median half-life decrease from end year 2005 (i.e. 1999-2005) to end year 2009 (i.e. 2003-2009), and then recover to its initial level in end year 2012 (i.e. 2006-2012). There is no upward trend for either the mean or median half-life throughout those years. Second, the grey line in Figure 6 shows that the number of significantly convergent products was increasing over the period, which provide more supportive evidence of increasing market integration in China. However, both the mean and median lines show that the declining trend of the half-life (i.e. faster convergence) stops around end year 2009 (i.e. 2002-2009) and turn into an increasing trend in the half-life (i.e. slower convergence). We need to cautiously interpret this change in the trend: the increase in the half-life does not necessarily mean the market is fragmented, but it necessarily implies that trade costs became larger.

Figure 7 shows the moving average of the mean half-life by category, and the empirical patterns are consistent with that in Figure 6. For these four categories (perishable consumer goods, nonperishable consumer goods, raw industrial materials and processed industrial materials), each of them witness a change in the direction of the trend around end year 2009. Here, it is not clear what the determinants are behind the change in the rate of price convergence. Candidate explanations are the tariff change required by WTO, the industrial policy imposed by the local government, and the reform implemented on the SOEs. But, at least, this study shows that China's rapid economic growth is not necessarily associated with increasing market integration.

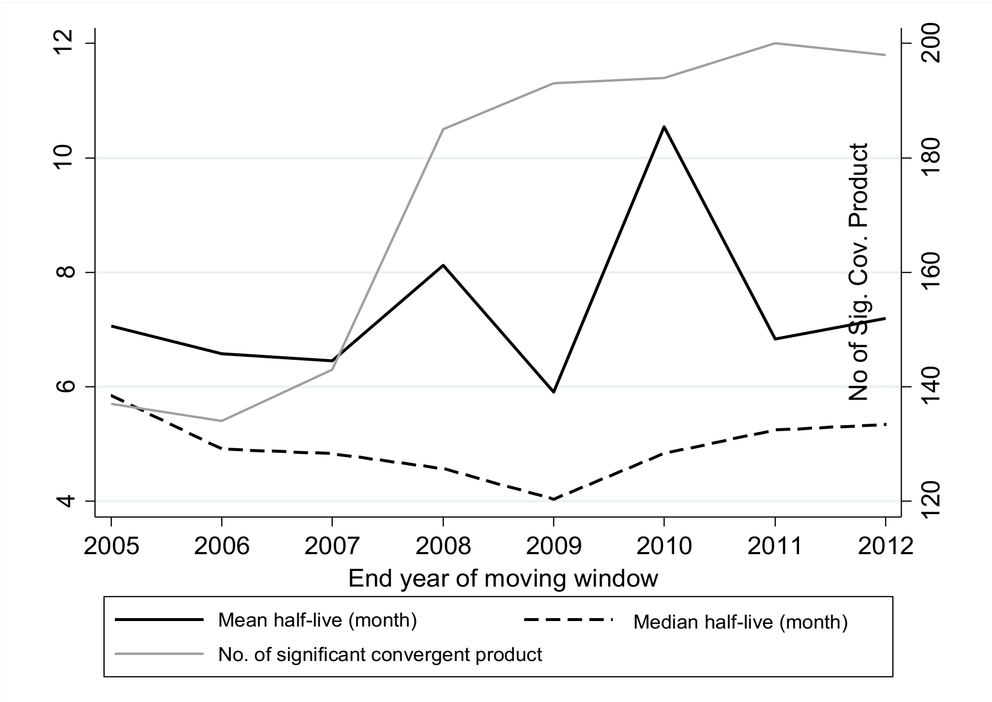

Fig.6 Dynamic Average Half-life (7-year-rolling window)

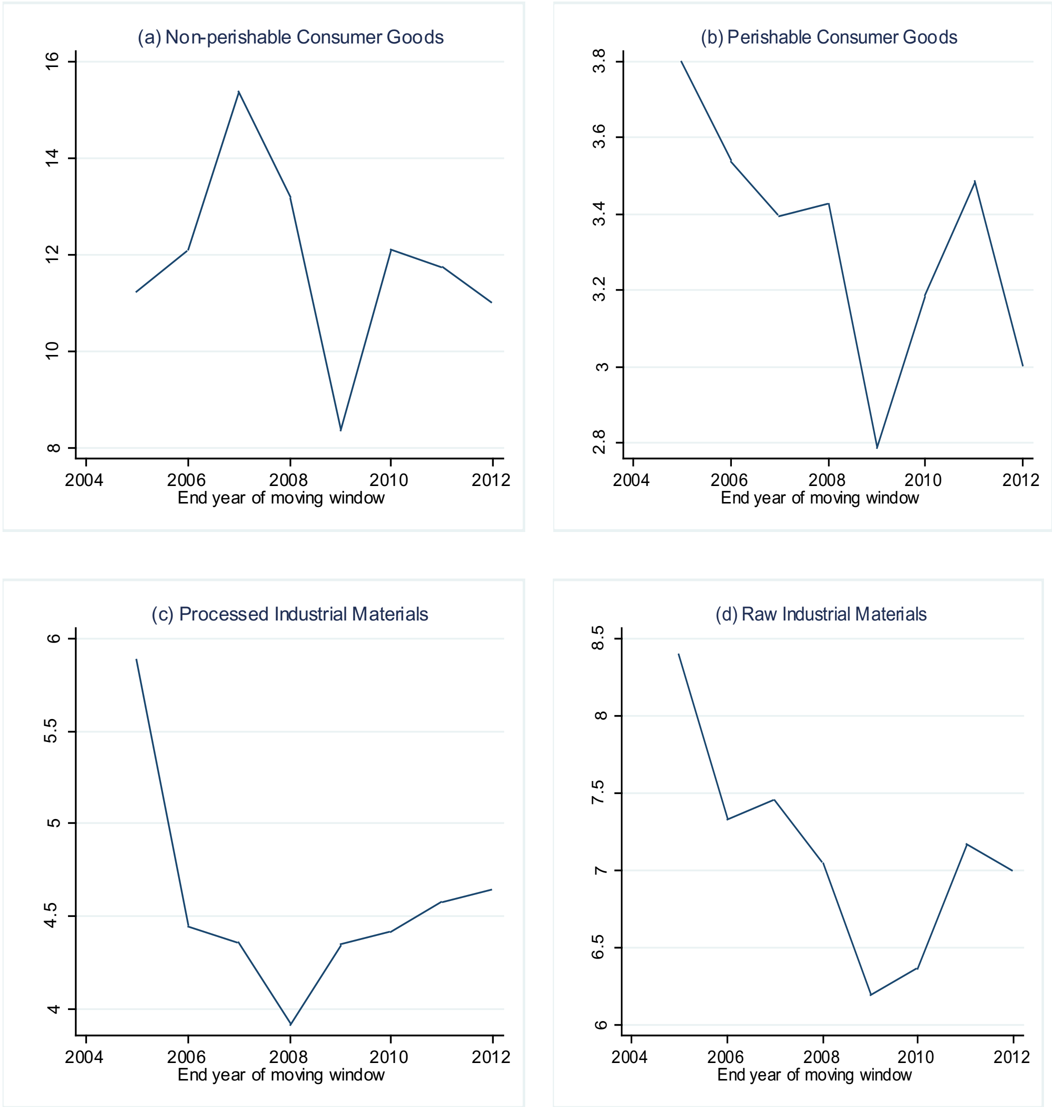

Fig.7 Dynamic Average Half-life (by category, 7-year-rolling window)

V.3 The Determinants of Price Dispersion

The previous subsections examine price convergence based on panel unit root methods (i.e. MG-CCE), which describe the convergence speed of homogeneous commodity prices across different regions in the long run. In this section, we examine the determinants for price dispersion, which enable us to identify the determinants of dynamic price co-movement. Following regression (5), the baseline results are reported in Table 4.

In the "overall" column of Table 4, price dispersion is used as the dependent variable and is measured using all products for each city-pair in each month. In the rest of the columns, price dispersion is measured using different categories separately. There are three consistent findings throughout all columns: first, the log of distance is significantly positive, which is in line with the intuition that transportation costs are positively related to the price convergence (Parsley and Wei, 2003; Ceglowiski, 2003). Second, the coefficients for the yearly trend are significantly positive in all columns except for perishable consumer goods, which imply the rising trend in price dispersion. This contradicts our previous results based on the panel unit root test. Third, the big cities and coastal dummies are negative and significant in all columns. These show that price dispersion is smaller between the more developed cities.

The coefficients of distance and trend variables in Table 4 appear to contradict our the results in Table 3. We find an upward trend for price dispersion and a significant impact from distance in Table 4 while we also find the significant convergence for most of the goods in Table 3. Caution should be taken in interpreting these results: an increase in a commodity's price dispersion through distance or time within a certain band does not contradict the LOP (Fan and Wei, 2006). The finding of an increasing in price dispersion is consistent with Wu and Zhu (2015)'s argument that the similarity of industrial policy between local governments defers the process of specialization across regions and implicitly leads to the market fragmentation. Empirically, the increasing in trend for price dispersion, documented in Table 4 for most categories, supports our previous results in Figure 7 that the rate of convergence for many goods has slowed since end year 2009.

Table 4
Regressions on the Determinants of Price Dispersion

Dependent variable: $S_{ij,t}$

	Overall	Perishable Consumer Goods	Nonperishable Consumer Goods	Processed Agricultural Materials	Processed Industrial Materials	Raw Industrial Materials
$\ln(Dis)_{ij}$	0.043	0.0685	0.0115	0.0202	0.0101	0.0148
	(0.0009)***	(0.001)***	(0.0013)***	(0.0011)***	(0.0006)***	(0.0012)***
Year_trend	0.0096	-0.0079	0.028	0.0135	0.0017	0.0122
	(0.0001)***	(0.0001)***	(0.0002)***	(0.0004)***	(0.0001)***	(0..0002)***
Big Cities Dummy	-0.0219	-0.0106	-0.0219	-0.004	-0.0097	-0.0099
	(0.0015)***	(0.0014)***	(0.0025)***	(0.0021)*	(0.0013)***	(0.0027)***
Coastal Dummy	-0.0068	-0.0109	-0.0018	-0.0031	-0.0037	-0.0065
	(0.0015)***	(0.0013)***	(0.0024)	(0.0018)*	(0.0012)***	(0.0022)***
City *i* and *j*'s fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1478042	1297491	1165679	481940	1148834	1011422
Adjusted R^2	0.3339	0.4034	0.3979	0.1107	0.1374	0.2676

Note: Standard errors clustered by each city pair and are in parenthesis; Constant variable is not reported in this table; *,**,*** represent significance at 10%, 5% and 1% level.

The coefficients for big cities dummy and coastal dummy show a different story from Fan and Wei (2006). Fan and Wei (2006) hypothesize that city pairs where both cities opened earlier and developed faster should experience smaller price dispersion, but they cannot find consistent evidence that the coastal dummy is negative. Since our data's geographical coverage is much larger than Fan and Wei (2006), we are able to construct the big cities dummy as well as the coastal dummy to pick up the effects of city pairs where both cities are quite developed (in the list of 36 first-tier cites) or are in the coastal regions. The consistent significant and negative coefficients for the big cities dummy and the coastal dummy strongly indicate that price convergence is more prevalent between the more developed cities.

Table 5

Regressions on the Determinants of Price Dispersion (2)

Dependent variable: $S_{ij,t}$

	Overall	Perishable Consumer Goods	Nonperishable Consumer Goods	Processed Agricultural Materials	Processed Industrial Materials	Raw Industrial Materials
$\ln(\text{Dis})_{ij}$	0.0518	0.0834	-0.0031	0.0196	0.0072	-0.0176
	(0.0013)***	(0.0012)***	(0.0024)	(0.0022)***	(0.0011)***	(0.0024)***
$\ln(\text{Dis})_{ij}$*Year_trend	-0.001	-0.0019	0.0017	0.0002	0.0004	0.0045
	(0.0002)***	(0.0001)***	(0.0003)***	(0.0005)	(0.0002)***	(0.0003)***
Year_trend	0.0168	0.0051	0.0159	0.0124	-0.001	-0.0192
	(0.0011)***	(0.0006)***	(0.0019)***	(0.0034)***	(0.001)	(0.0021)***
Big Cities Dummy	-0.0219	-0.0106	-0.0219	-0.004	-0.0097	-0.0104
	(0.0015)***	(0.0014)***	(0.0025)***	(0.0021)*	(0.0013)***	(0.0027)***
Coastal Dummy	-0.0066	-0.0106	-0.0022	-0.0032	-0.0037	-0.0071
	(0.0014)***	(0.0013)***	(0.0024)	(0.0018)*	(0.0012)***	(0.0022)***
City *i* and *j*'s fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1478042	1297491	1165679	481940	1148834	1011422
Adjusted R2	0.3345	0.4063	0.3984	0.1107	0.1376	0.2731

Note: Standard errors clustered by each city pair and are in parenthesis; Constant variable is not reported in this table; *,**,*** represent significance at 10%, 5% and 1% level.

Since we are concerned with dynamic changes in China's market integration, we investigate the degree to which trend of price dispersion is explained by transportation costs, which are captured by the interaction between the distance variable and annual trend in Table 5. In the overall column of Table 5, this interaction term is negative and significant, which implies transportation costs have been declining over time. However, after controlling for the interaction term between distance and trend, the trend variable is still positive and significant. For the results disaggregated by category, only perishable goods have a negative coefficient on this interaction term. The signs for the other categories are positive and most of them are significant. This pattern indicates that more and more of price dispersion should be attributed to transportation costs or trade costs related to distance. After controlling for the interaction between distance and trend, trend variable remains positive and significant except among raw industrial materials. This finding means geographical distance can only partially explain why price convergence became slower.

VI. Summary and Conclusions

Since the 1980s, China has successfully transitioned from a complete planned economy into an economy with a 40-year history of high economic growth. In this process, China's prices have been gradually liberalized through the dual-track system. China's highly centralized political system as well as its gradual reform suffer from the suspicion of a side-effect of GDP competition - local protectionism. This debate depends on evidence of the LOP in China. Since China became a WTO member in 2001, it has witnessed much faster economic growth, larger trade and investment liberalization, and more domestic reform. Has China's market become more fragmented after 2001? Using a highly disaggregated price dataset, this study is the first research to investigate China's LOP using data up to the year 2012, which provides new evidence regarding whether China is integrated, and investigates the determinants of Chinese integration.

By applying the MG-CCE model of panel convergence analysis introduced in Pesaran (2006), our empirical study examines price movements in China with a large data set that consists of 290 products in 173 cities over the 1997-2012 period. To the best of our knowledge, this study represents the first application of the second-generation panel unit root test (i.e. allowing for heterogeneity as well cross-section dependence) to evaluate contemporary China's market performance. This study not only enriches the LOP literature by adding new evidence with new data and methodology, but also sheds new light on the debate whether China's market is fragmented by local government protection and intervention.

Two main findings emerge from this empirical study. First, for an overwhelming majority of the goods and services, their prices do converge to the LOP. In comparison with Fan and Wei (2006)'s results, our MG-CCE estimate allows for heterogeneity, common correlated effects, as well as seasonality, and suggests that China's rate of convergence to the LOP has been over-estimated in the previous literature. Second, in our dynamic estimates, we identify an upward trend for price dispersion and a downward trend in the rate of convergence since the 21st century. Based on these findings, we have to review how China's gradual reform and economic growth affect market performance. We do not find China's economic growth is necessarily associated with faster price convergence. At the same time, our results challenge the conventional wisdom that China's gradual reform will eventually lead to the local protection and market fragmentation.

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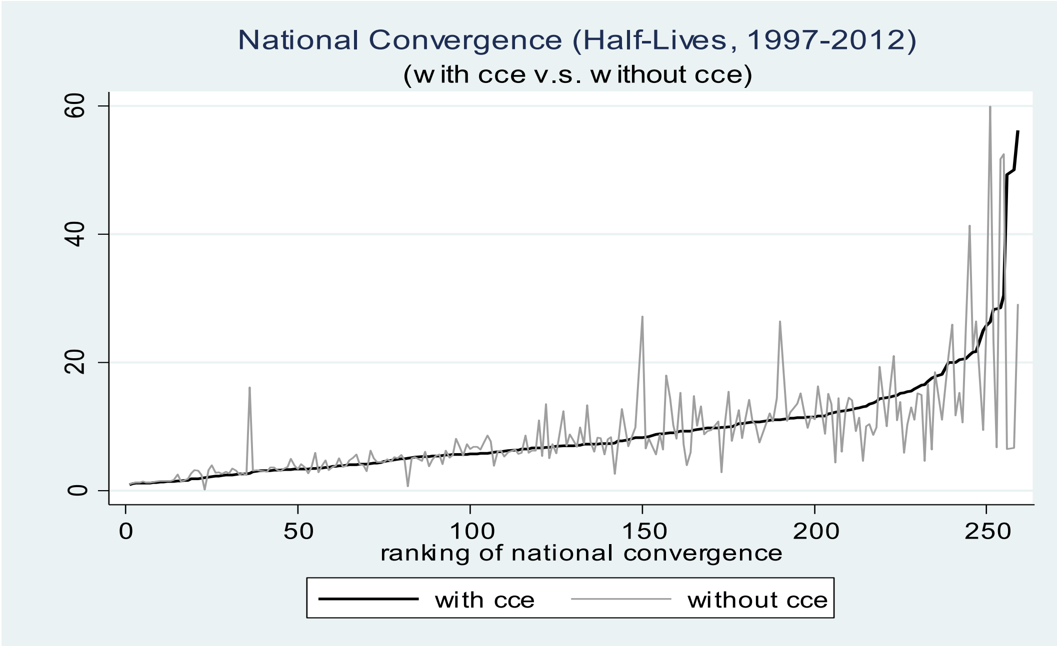
Appendix 1: Descriptions of Commodities Included

Table A.1 Product Names, Sample Size and Basic Description (Sample data)[9]

Product Name	Time Range	City No.	Obs.	Mean	SD
Energy					
Diesel oil (No.-10, purchasing price)	2006m1-2012m11	37	2278	6785.71	1394.52
Diesel oil (No.-10)	2005m1-2012m11	43	2690	6825.90	1577.05
Gasoline (No.90 clean, purchasing price)	2001m8-2012m11	61	6017	6064.22	1842.09
Gasoline (No.90 clean)	2001m8-2012m11	61	6367	6495.80	1881.70
nonperishable consumer goods					
White wine (500ml,52%,top grade)	1997m1-2012m11	143	8990	490.31	325.33
White wine (500ml,52%,middle and low grade)	1997m7-2012m11	145	7497	69.59	116.70
Refrigerator (refrigerator)	2000m1-2012m11	154	16973	2940.86	665.21
Color TV (color TV)	2000m1-2012m11	154	16338	3212.69	1398.40
perishable consumer goods					
White granulated sugar (bagged)	1997m1-2012m11	160	19836	2.90	1.17
Rapeseed oil (barreled)	1997m1-2012m11	154	16391	7.34	13.96
Grass carp (about 1000g, live)	1997m7-2012m11	159	19758	5.55	1.79
Eggs (fresh,intact,from chicken farms)	1997m1-2012m11	160	21147	3.23	0.92
processed agricultural materials					
Dichlorvos (80%,Emulsion)	1997m7-2012m11	147	8617	18.81	4.05
LDPE mulching film (0.014mm±0.002 thick)	1997m1-2012m11	143	7509	9.58	2.13
LDPE greenhouse film (folding radius:1m ,0.10mm±0.02 thick)	1997m1-2012m11	144	7391	9.89	2.73
Carbalmide (Nitrogen content 46%,domestic)	1997m1-2012m11	147	9120	1.46	0.34
processed industrial materials					
Flat steel (4×30,Q235)	1997m7-2003m3	145	7607	2600.84	318.24
Channel steel (30,Q235)	1997m7-2003m3	141	7493	2853.50	381.18
Galvanized sheet (0.5,200g)	1997m1-2003m3	143	8029	5416.22	660.55
Galvanized sheet (0.75,200g)	1997m7-2005m12	149	10887	5548.69	805.71
raw industrial materials					
Benzene (pure benzene)	1997m7-2012m11	126	10013	5215.76	2522.70
Soda ash (industrial sodium carbonate,content≥98.5%)	1997m1-2012m11	147	17245	1555.85	382.91
LDPE (thin film,1F7B)	1997m1-2012m11	147	14612	9869.32	2564.41
Domestic plywood (ordinary 1.22×2.44×3)	1997m7-2012m11	151	13956	28.86	33.84
services					
Coach ticket (passenger transportation)	2002m1-2011m12	142	10761	0.21	0.55
taxi rental fare (ordinary taxi)	2002m1-2012m6	145	12180	1.59	0.57
Students apartment (Comprehensive university,four-bed room)	2003m4-2012m6	137	8983	1017.27	290.19
Sewage treatment fee (domestic sewage treatment fee)	2002m1-2012m6	144	11439	0.54	0.26

Appendix 2: with CCE v.s. without CCE

[9] To save the space, 4 selected products are reported in each category. The full sample is available on request.


National Convergence (Half-Lives, 1997-2012)
(w ith cce v.s. w ithout cce)
60
40
20
0
0
50
100
150
200
250
ranking of national convergence
with cce
without cce