China Economic Review xxx (2012) xxx–xxx

Contents lists available at SciVerse ScienceDirect

China Economic Review

Chinese manufacturing on the move: Factor supply or market access?☆

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ARTICLE INFO

Article history:
Received 20 December 2011
Received in revised form 15 August 2012
Accepted 29 August 2012
Available online xxxx

Keywords:
Locational change of industries
Factor supply
Market access

JEL classification:
L6
R12
R3

ABSTRACT

This paper examines recent trends in the location of manufacturing activities in China using a model that combines forces relating to Heckscher–Ohlin (H-O) and New Economic Geography (NEG). It is found that there are large intercity shifts in industrial employment since 1998 in China, with the overall redistribution being towards coastal cities. Our investigation of the determinants of locational change in Chinese industries suggests that market access based on NEG theories played a key role in industrial location especially in the post-WTO period, while there is evidence of H-O arguments associated with factor supply in previous years.

1. Introduction

The rising costs of land and labor in the coastal regions and the consequent inland shifts of some manufacturing industries in China have generated considerable public attention. As shown in an article in China Daily, “China has seen more and more manufacturing companies moving their plants to or setting up new plants in the country's interior from coastal provinces as factory owners try to cut costs. Higher labor and realty prices made China's traditional manufacturing bases, like the mainland's top exporting province of Guangdong, less advantaged than before. However, inland provinces and cities that offered improved transportation capacities and preferential policies shine as new investment destinations”(Xinhua, 2010). However, recent studies illustrate that most manufacturing industries in China are still highly concentrated in coastal areas such as the Yangtze River Delta and the Pearl River Delta, and the trend of such concentration has intensified during the post-WTO period (see Barbieri, Di Tommaso, & Bonnini, 2012; He & Wang, 2012). This confronts us with the question: why is coastal China still favored as the optimal location for manufacturing firms despite the rising land rents and wages in these regions? To investigate this question this paper documents the interregional redistribution of manufacturing industries in China over the past decade and examines the forces that drove this redistribution.

There are several explanations for the location of industries. One standard explanation is based on Heckscher–Ohlin (H-O) theory, arguing that a region attracts those firms that use its relatively abundant factor. In line with this view, the location of firms is attributed to exogenous factor supplies. Another possible explanation is implied by models of New Economic Geography (NEG),

☆ We thank Jane Golley and the anonymous referee for insightful comments and suggestions. We also thank the participants in the 4th Transition and Development International Conference 2011 (Fudan University) for helpful comments on this paper. Jianfeng Wu acknowledges financial support from National Natural Science Foundation of China (71003026). Zhao Chen acknowledges financial support from National Social Science Foundation (11AZD084). Both Jianfeng Wu and Zhao Chen thank the support from Fudan Workshop of China Economic and Social Studies.

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1043-951X/$ – see front matter © 2012 Elsevier Inc. All rights reserved.
http://dx.doi.org/10.1016/j.chieco.2012.08.005

which predict that firms are likely to locate in established industrial centers because of the presence of greater demand or because of externalities arising from labor-market interactions, from input–output linkages, or from knowledge spillovers (see Krugman, 1991a,b). According to NEG theory, firms wish to locate near large markets to exploit external economies relating to market access. There is no shortage of empirical studies gauging the relative importance of market access and factor supply for the location of industries in advanced economies. Some authors argue that H-O-type factor supply is very important in determining the location of industries.[1] Other literature lends support to the argument that NEG-type market access has been the primary factor influencing industrial location (Davis & Weistein, 2003; Klein & Crafts, 2011; Wheat, 1986). For example, Klein and Crafts (2011) investigate the changes in industrial location in the United States over the period 1880–1920. Following the methodology of Midelfart-Knarvik, Overman, Redding, and Venables (2000), they regress the industrial output share for an area against a set of H-O- and NEG-type interactions between industry and location characteristics. They find substantially stronger evidence of market access, which manifests itself through interactions with both scale economies with linkage effects.

Motivated by these earlier studies, this paper tests empirically whether arguments relating to H-O and NEG models are consistent with recent trends in the location of manufacturing activities in China. The methodology in this paper is similar to that of Klein and Crafts (2011), which relies on an estimation equation incorporating both factor supply and market access determinants of location. But our study differs from their paper in three respects. First, Klein and Crafts (2011) empirical model suffers from endogeneity issues arising from the reverse causality between local industry employment growth and market access. In our study, we use each area's relative employment growth for an industry, which is the difference between the actual employment level of a particular industry in an area at the end of the period and what the level would have been if the area had grown at the national rate, as the dependent variable. Locational characteristics in terms of market access can be assumed to be exogenous to such relative growth of employment, thus overcoming the endogeneity problem. Second, they estimate the pooled data with 48 states and 19 industries separately for each census year during the period of 1880–1920 using OLS, which may lead to less efficient estimators when the regression disturbances are correlated across various years. In this paper, we estimate the model as a system of seemingly unrelated regression (SUR), which allows for these inter-temporal correlations. Third, we introduce an exogenous shock, China's accession to the WTO in 2001, to identify the driving mechanisms behind recent changes in the location of Chinese manufacturing activities. China's entry into the WTO has strengthened its domestic and international markets with more liberalization of trade in goods and services, more foreign investment inflows, and fiercer market competition. Concurrently, the rising cost of land, labor, and natural resources in the coastal areas has shifted some industries toward the inland cities (as seen in Section 2 below). Investigation of the locational change of manufacturing firms and their determinants before and after accession to the WTO may therefore enrich our understanding of the dynamics of industrial location in China.

Using the Annual Survey of Industrial Firms (ASIF) dataset for 1998–2009 conducted by National Bureau of Statistics (NBS) in China, our study finds that there has been substantial redistribution of employment for 3-digit industries towards coastal cities, especially during the post-WTO period and despite some evidence of inland shifts for labor-intensive industries. We investigate the factors that are continuing to favor coastal cities as optimal locations for firms. The empirical results show that recent trends in the location of industries in China have been jointly influenced by forces of factor supply and market access, with the effect of the latter stronger in the post-WTO period.

The reminder of this paper is organized as follows. Section 2 presents data, measurement, and intercity shift in patterns of industrial employment in China between 1998 and 2009. Section 3 presents the empirical framework for explaining the sources of change in industrial location over this period. Section 4 estimates the impacts of factor supply and market access on changes in industrial location and quantifies their relative importance. Section 5 concludes.

2. Intercity redistribution of industries in recent China

2.1. Measurement and data

Our method for calculating interregional shifts in industrial employment is from Fuchs (1962). The index of redistribution of industries is based on the regional comparative gain or loss of an individual industry, which is defined as

$$\mathrm{RGROWTH}_{i,k,t-t_0} = X_{i,k,t} - X_{i,k,t_0}\frac{X_{k,t_0}}{X_{k,t}}\quad , \tag{1}$$

where X_{i,k,t_0} is the level of employment in industry $k=1,\ldots,n$ for region i in the initial year t_0 and $X_{i,k,t}$ is the corresponding level at the end of a given period. X_{k,t_0} and $X_{k,t}$ are the national levels of employment in industry k in the first and final years, respectively. According to this definition, locational change is not the physical movement of an industry from one region to another, but the difference between the actual level of an industry in a region at the end of the period and what the level would have been if the region had grown at the national rate. If a region grows faster than the whole nation, $X_{i,k,t} - X_{i,k,t_0}\frac{X_{k,t_0}}{X_{k,t}} > 0$, then that region has experienced a "comparative gain." If the region grows slower, the difference between the actual level and the hypothetical level is a "comparative loss."

[1] Fuchs (1962) documents that access to local natural resources was central to the 1929–1954 change in the location of manufacturing industries in U.S. Other studies using U.S. data that also conclude that factor supply matters for industrial location include Ellison and Glaeser (1999) and Kim (1995,1999).

Next we calculate the extent to which an industry shifts across regions by summing all the comparative gains or losses across regions using an index of redistribution as follows:

$$\mathrm{SHIFT}_k = \frac{\sum_i |\mathrm{RGROWTH}_{ik}|}{2}, \tag{2}$$

Hence, SHIFT measures the percentage of total industry employment that would have to be redistributed across regions in order to make the distribution at the end of the period the same as it was in the initial year.

To calculate the extent of interregional shift for industries in China, we employ the Annual Survey of Industrial Firms (ASIF) dataset produced by the NBS for the period 1998–2009. This dataset contains all state-owned enterprises (SOEs) and non-state-owned enterprises with annual sales of more than 500 million yuan. The dataset provides detailed information on firms' identification, operations and performance, including location, industry code, and employment. Industry in this dataset is defined to include mining, manufacturing and public utilities. The focus of our study is on manufacturing. Table 1 reports statistics on employment, industrial output and value added for our firm-level data. For all of these variables, there is a clear upward trend, indicating that manufacturing firms in China have experienced rapid growth over the sample period. There are two big jumps in 2004 and 2008 since these two years are industry census years with more comprehensive survey coverage. The 1998 employment data for two regions, Gansu and Jilin, are not available in the ASIF dataset. As a result, the data for 1998 does not include the firms from these two provinces. In addition, in this analysis we exclude the firms for all years from Tibet due to inadequate data.

The geographical unit of analysis is prefecture-level-and-above city. For each firm in the ASIF dataset, there is information on the address and the code and name of the county, prefecture and province where it is located. The prefecture level-and-above city is preferable for two reasons. First, as China has experienced incremental economic reform and differentiated globalization processes across regions, the impacts of regional endowments and market access on industrial growth may be more localized and conditional on the process of economic transition (He & Pan, 2009). This means that the relationship between local characteristics and industrial location is likely to hold at a finer spatial scale. Hence, it is better to consider sub-provincial spatial units as we do here. Second, administrative boundaries at the city level have experienced fewer significant changes than those at the county level over the sample period (Lu & Tao, 2009). In this analysis, a total of 220 prefecture-level-and-above cities are included.[2]

To study the intercity shift of industrial activities, we also need information on firms' primary industry codes. For each firm in the ASIF dataset, we can attain the information on its primary 2-digit, 3-digit, and 4 digit industry codes. In this study, we consider the redistribution pattern for each 3-digit industry by aggregating firms' employment data for two reasons. One is that extensive external economies are found within 3-digit categories (Wen, 2004). The other is that less spatial shift is observed for more aggregated categories due to the large average size of Chinese cities. In total there are 163 3-digit industries considered in the results presented below.[3]

2.2. The redistribution of industries across cities in China

To examine whether entry into the WTO has affected trends in the location of industries in China, in the analysis to follow the patterns of redistribution of industries are presented for two time periods, 1998–2001 and 2002–2009. Obviously, the results can be influenced by the choice of an interval. The ideal measure of interregional shift during an interval is one for which the change between initial and terminal year is independent of cyclical movements within that interval. The 1998–2001 and 2002–2009 intervals are chosen since they are sufficient to infer the impact of the accession to the WTO on industrial development while not being sensitive to cyclical amplitudes.[4]

We calculate the magnitudes of intercity shift for each industry using the index of interregional redistribution SHIFT introduced in Section 2.1. According to Catin, Luo, and Van Huffel (2005), we divide these 163 industries in China into three larger categories: high-tech, labor-intensive, and resource-based industries. We present the means and standard deviations of the magnitudes of interregional shift across these three different categories of industries for the two time periods in Table 2. It is found that shift – in terms of number of workers – was largest in labor-intensive industries in the first period of 1998–2001. High-tech industries experienced the largest shift in the later period of 2002–2009. The mobility of resource-based industries is found to be relatively lower than that of the other two groups of industries in both time periods. The heterogeneity in the magnitudes of shift suggests that the responses to China's entry into the WTO may be related to industrial characteristics.

[2] There are some problems caused by the changes in administrative boundaries in China and consequent codes of counties during the period 1998–2009. For example, firms may misreport the codes of the county since they are not aware of these changes in the annual surveys of industrial firms. Even if the county codes are reported correctly, they may not be comparable across years due to these changes. We address these problems for cities following Lu and Tao (2009). First we check the accuracy of the county codes based on the address firms reported. Then we convert the county codes of all firms to the benchmark system of county codes, which is based on 2002 National Standard of Administration (GB/T 2260-2002).

[3] The classification system for Chinese industry codes in 1994 (GB/T4754-1994) was replaced by a new one (GB/T 4754-2002) in 2003, which led to an inconsistency problem for industry codes over the sample period. To solve this problem, we convert the industry codes for firm-level data between 1998 and 2002 to the new classification system (in the case of an old 4-digit code corresponding to a new 4-digit code or allocating some old 4-digit codes into the new 4-digit code corresponding to their products (see Lu & Tao, 2009)). Furthermore, we drop some 3-digit-level industries on which the information is missing in the ASIF dataset for some particular years.

[4] For example, Brandt, Biesebroeck, and Zhang (2012) provide the evidence of a big jump in firm-level total factor productivity growth after China's entry into the WTO in 2001.

Table 1
Summary statistics on the ASIF firm-level dataset.

Year	Number of firms	Employment	Output	Value added
1998[a]	145,951	46.30	5.40	1.52
1999	147,098	47.60	6.09	1.69
2000	148,260	44.50	7.14	1.97
2001	155,394	44.10	8.10	n.a
2002	166,857	46.20	9.75	2.63
2003	181,185	48.80	10.23	3.41
2004	256,999	57.30	17.50	n.a
2005	251,494	59.60	21.80	5.72
2006	279,236	63.30	27.50	7.24
2007	313,024	68.50	35.40	9.04
2008	382,862	74.20	42.60	n.a
2009	327,658	66.60	42.00	n.a

[a] For Year 1998, firms from Gansu and Jilin are excluded due to missing data on employment. The firms included in this analysis are limited to the manufacturing sector. All values of output and value added are denoted in trillion yuan and employment in millions of employees. n.a. indicates that no data on value added are available that year. Source: the ASIF dataset.

Table 2
Magnitudes of intercity employment shifts for different categories of industries (number of workers).

	1998–2001					2002–2009				
	Number of industries	Mean	STDEV	Min	Max	Number of industries	Mean	STDEV	Min	Max
All industries	163	52,787	57,120	0	318,266	164	75,906	91,642	0	500,248
Labor-intensive industries	117	57,589	63,990	0	318,266	118	74,751	92,015	0	500,248
High-tech industries	28	42,076	30,628	0	120,431	28	97,356	109,446	4,009	450,463
Resource-based industries	18	38,239	33,000	0	136,468	18	50,117	41,942	117	165,007

Calculated by the authors. The number of industries indicates the number of 3-digit sectors included in each category of industries. This table reports the means, standard deviations, minimum and maximum of the intercity employment shifts across different categories of industries in the period of 1998–2001 and 2002–2009, respectively. Source: the ASIF dataset.

A closer look at the comparative gains or losses, RGROWTH, in the number of employees for each city provides insights into both the extent and the direction of changes in industrial location. We classify these 220 cities into three groups: Coastal cities, Central cities, and Western cities.[5] Table 3 presents the sum of comparative gains or losses of individual industries by these three group regions in the two periods, 1998–2001 and 2002–2009, respectively. In the first period, the coastal and western cities enjoyed comparative gains, whereas the central cities suffered comparative losses. In the second period, the coastal cities enjoyed comparative gains, while both central and western cities suffered comparative losses. The aggregated data suggests that the principal phenomenon since China's entry into the WTO has been the shift of manufacturing towards coastal areas. However, evidence of inland-oriented shifts for some labor-intensive industries can be found when we consider the regional comparative gains or losses of individual industries (see Appendix Tables 1, 2 and 3).

3. Determinants of changes in industrial location: Empirical framework

The preliminary analysis above suggests that a test of the determinants of change in industrial location should consider both industry and location characteristics. Theoretically there are two competing but not mutually exclusive hypotheses on the determinants of industrial location. The Heckscher–Ohlin (H-O) model implies that the distribution of economic activity is determined by regional factor supply. The theories of New Economic Geography (NEG) argue that firms tend to concentrate in industrial centers in order to exploit external economies related to access to large markets. Following the empirical work cited above (e.g., Klein & Crafts, 2011; Midelfart-Knarvik et al., 2000) we explain the change in the location of industries in China by looking at the relative importance of H-O- and NEG-force interactions between location and industry attributes. We first define and measure the location and industry characteristics of interest. We then document the empirical framework and its implementation.

[5] The coastal cities are those in Beijing, Tianjin, Shanghai, Liaoning, Hebei, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan, and Guangxi. The central cities include those locating within Jilin, Heilongjiang, Shanxi, Anhui, Jiangxi, Henan, Hubei, Hunan, and Inner Mongolia. The western cities are those in Sha'anxi, Gansu, Qinghai, Ningxia, Xinjiang, Sichuan, Chongqing, Guizhou, and Yunnan.

Please cite this article as: Bao, C., et al., Chinese manufacturing on the move: Factor supply or market access? *China Economic Review* (2012), http://dx.doi.org/10.1016/j.chieco.2012.08.005

Table 3
Comparative gains or losses for three groups of cities (number of workers).

	1998–2001	2002–2009
Coastal cities	901,475	2,828,975
Central cities	−618,084	−374,489
Western cities	12,218	−80,936

Calculated by the authors. All values indicate the sum of comparative gains or losses in the number of employees across individual industries by geographic division. Source: the ASIF dataset.

3.1. Location and industry characteristics

Here we develop proxies for a list of location and industry characteristics. One of the location characteristics of interest is market access. According to Harris (1954), we calculate market access based on a city's GDP using the following formula:

$$\text{Maccess}_i = \sum\nolimits_{l \neq i}^{R} \text{GDP}_k * e^{-\left(\frac{d_{il}}{\text{sd}}\right)^2}, \tag{3}$$

where d_{il} is the spatial distance between city i and its trading partner l and sd is the standard distance computed as the distance between two major cities in China, Beijing and Shanghai. For a city, market access is defined as the inverse distance-weighted sum of GDP for its surrounding cities, indicating the extent to which a city has access to other markets. The second location characteristic is a city's access to a relatively cheap labor force measured by agricultural employment share (denoted as Agrshare). The data on both of these indicators are drawn from Urban Statistics Yearbook for 1999–2010 complied by NBS. Table 4 displays the means and standard deviations for these two variables associated with city characteristics in 1998 and 2002, respectively. Two points stand out. First, there is an increasing trend in market access but a declining trend in agricultural employment share. This is consistent with China's rapid urbanization in recent years (Huang & Luo, 2009). Second, the statistical evidence for these two variables illustrates different patterns across groups of cities: coastal cities tend to have the highest levels of market access and lowest levels of agricultural employment shares.

To evaluate the determinants of changes in industrial location, we consider five indicators for industry characteristics, two related to H-O-type factor supply and the other three associated with NEG-type market access. More specifically, two indicators that proxy for factor supply are labor wage share (denoted as Labwage), measured in the labor wage income relative to industrial value added,[6] and labor input intensity (denoted as Labemp) measured as thousands of employees per yuan of industrial value added.[7] Both of these two indicators measure the extent to which an industry depends on the labor force.

For the three indicators of market access, we first consider a proxy for intermediate input use, which predicts that industries with high intensity of intermediate input use are likely to locate in regions with large market access. Since this information is not directly available in the ASIF dataset, we construct intermediate input intensity as follows:

$$\text{Inter}_k = \frac{\text{OUTPUT}_k - \text{VA}_k}{\text{OUTPUT}_k}, \tag{4}$$

where OUTPUT_k and VA_k are the total production output and value added for industry k.[8]

The second variable related to industrial characteristics of market access is labor force specialization. Rosenthal and Strange (2001) use three indicators to proxy for labor force specialization: labor productivity, the percentage of management staff in total employment, and the share of workers with doctoral, master's, and bachelor's degrees. In the ASIF dataset, the information on the education level of employees is not available and the separation of employees into management staffs and production workers is also not provided. Instead, assuming that the wage level in competitive industries is commensurate with the skill level we construct a proxy for the importance of labor force specialization as follows:

$$\text{Labspe}_k = \frac{\text{WAGE}_k}{\text{EMP}_k}, \tag{5}$$

where WAGE_k and EMP_k are industry k's total wage and employment, respectively. This indicator measures the real wage rate for an industry. The higher this indicator, the higher the skill level required in this industry and the greater the need for labor market pooling. Thus, we hypothesize that industries with high levels of labor force specialization tend to locate in areas with large market access.

The third variable is technology intensity. Previous studies have used the proportion of R&D expenditure in total sales at the industry level to proxy for the importance of technology spillovers (see Audretsch & Feldman, 1996). Unfortunately, the ASIF data set does not include firms' R&D expenditure data. Following Lu and Tao (2009) we construct a more comprehensive and

[6] We utilize information on the wages and employee supplementary benefits reported by firms in ASIF dataset to generate total labor wage.
[7] Poncet (2005) adopts a similar proxy but she uses industrial output instead of industrial value added.
[8] This indicator is also employed in Amiti (1999).

Table 4
Summary statistics for area characteristics.

		1998		2002	
		Mean	STDEV	Mean	STDEV
Market access Maccess (million yuan)	Costal	19.60	0.15	19.97	0.14
	Center	19.55	0.29	19.93	0.26
	Inland	19.26	0.34	19.62	0.31
Agricultural employment share Agrshare (percent)	Costal	4.17	19.05	2.26	3.44
	Center	8.18	11.31	5.01	0.26
	Inland	4.61	9.57	2.96	3.92

This table reports the values of mean and standard deviations for area characteristics in 1998 and 2002 by three groups of cities: the coastal, central and inland cities, respectively. Source: Urban Statistics Yearbook for 1999–2010.

outcome-based indicator, the share of new products value to total industrial output (denoted as Tech), to proxy for technology intensity as follows:

$$Tech_k = \frac{NPRODUCT_k}{OUTPUT_k} \Big/ \frac{\overline{NPRODUCT}}{\overline{OUTPUT}}, \tag{6}$$

which is the intensity of technology relative to the mean. $NPRODUCT_k$ is the value of new products for industry k. $\overline{NPRODUCT}$ and $\overline{OUTPUT}$ are the mean values of new products and output across industrial sectors. It is expected that industries with a high ratio of new product value to output will prefer areas with large market access.

We employ the information from the ASIF dataset to calculate all these indicators regarding industrial characteristics. For interest, we reveal the means and standard deviations of the indicators in Table 5. On average, the means for the majority of these five indicators were larger in 1998 than in 2002, with the exception of Inter, the intermediate input intensity. Moreover, the data show significant variations in the technology intensity Tech and labor force specialization Labspe in both 1998 and 2002.

3.2. Basic framework

Following the methodology of Klein and Crafts (2011) we build the empirical model to quantify the relevance of H-O- and NEG mechanisms in determining the location of industries in China over the period of 1998–2009. This methodology is theoretically grounded on the work by Midelfart-Knarvik et al. (2000), which points out that the location of an industry is determined by the interaction of industry and area characteristics. The reason for evaluating the interaction between area and industry characteristics lies in the fact that firms have different evaluations of the same kind of production factors. Industries will try to locate where their most important inputs are available, and will therefore be over-represented in that location. Industries for which the same production factor is less valued will instead be under-represented in those locations.

The model in our paper is fairly straightforward: the dependent variable is the relative employment growth for an industry in a city measured as comparative gain or loss RGROWTH. This is explained with mean reversion control for the initial level of employment plus interactions between location and industry characteristics of both H-O and NEG types. Area characteristics considered in this analysis include local agricultural employment share Agrshare and market access Maccess. Industry characteristics include measures of labor wage share Labwage, labor input intensity Labemp, intermediate input use Inter, labor

Table 5
Summary statistics for industry characteristics.

	1998		2002	
	(23,147 Observations)		(21,374 Observations)	
	Mean	STDEV	Mean	STDV
Labor force intensity (thousand workers, denoted as Labemp)	0.035	0.014	0.021	0.009
Labor wage share (thousand yuan, denoted as Labwage)	0.144	0.437	0.089	0.043
Intermediate input intensity (ratio, denoted as Inter)	0.704	0.087	0.711	0.073
Technology intensity (thousand yuan, denoted as Tech)	0.692	0.669	0.65	0.602
Labor force specialization (ratio, denoted as Labspe)	3,185	4,222	2,494	3,411

This table illustrates the number of observations, the means and standard deviations for industry characteristics in 1998 and 2002, respectively. Source: the ASIF dataset.

Please cite this article as: Bao, C., et al., Chinese manufacturing on the move: Factor supply or market access? *China Economic Review* (2012), http://dx.doi.org/10.1016/j.chieco.2012.08.005

force specialization Labspe, and technology intensity Tech. The estimation equation is as follows:

$$
\begin{aligned}
\mathrm{RGROWTH}_{i,k,t_0,t} = {} & \alpha + \beta_0 \mathrm{EMP}_{i,k,t_0} + \beta_1 (\mathrm{Agrshare} * \mathrm{Labwage})_{i,k,t_0} \\
& + \beta_2 (\mathrm{Agrshare} * \mathrm{Labemp})_{i,k,t_0} + \beta_3 (\mathrm{Maccess} * \mathrm{Inter})_{i,k,t_0} \\
& + \beta_4 (\mathrm{Maccess} * \mathrm{Tech})_{i,k,t_0} + \beta_5 (\mathrm{Maccess} * \mathrm{Labspe})_{i,k,t_0} \\
& + \textstyle\sum_j \gamma_j r_{i,j,t_0} + \sum_j \theta_j z_{k,j,t_0} + \varepsilon_{i,k,t_0},
\end{aligned}
\tag{7}
$$

where EMP_{i,k,t_0} is the level of employment in industry $k=1,\ldots,n$ for region i in the initial year t_0. The first two of these interactions are predicted by the traditional H-O argument associated with factor supply. The relative magnitudes and statistical significance of β_1 and β_2 illustrate the role of the agricultural employment share in affecting the locational changes of industries. The last three interactions highlight how an area's market access influences changes in industrial location. The first market access interaction predicts that industries that rely more on intermediate input use are likely to move towards areas with high level of market access. The second interaction indicates that industries with high levels of labor force specialization tend to locate in areas with large market access. The third market access interaction presumes that industries exhibiting technology intensity will gravitate towards locations close to large demand. γ_j and θ_j are the estimated coefficients of jth individual industrial characteristic $z_{j,k}$ and the area characteristic $r_{j,i}$, respectively.

4. Empirical results

4.1. Estimation issues

The main goal in this paper is to examine the factors influencing recent changes in the location of industries in China. If factor supply is important, we would see H-O-type interactions positively affect regional comparative gain or loss of an industry RGROWTH. If market access is important, NEG-type interactions would positively predict RGROWTH.

There are several estimation issues. One possible concern is reverse causality if local industry employment growth spreads to surrounding regions and contributes to local market access. However, in this analysis, we use the comparative gain or loss in a city for an individual industry (described above) as the dependent variable, which avoids this endogeneity problem since it is completely unrelated to measures of local market access. The second is to control for omitted variables. Obviously our data on location and industry attributes are limited in explaining relative employment growth in a region for an individual industry. To deal with this issue, we introduce both location and industry dummies replacing a list of location and industry characteristics. The third issue is the technique of estimating pooled data. In our data, there are two dimensions: industry k and city i, which may pose a heteroskedasticity problem. For example, we might face unobserved cluster effects arising from 220 city-level areas in China for 3-digit industries. To solve this problem, we introduce cluster-robust standard errors following White (1984) and Arellano (1997). However, cluster-robust standard errors assume that there is no correlation between unobserved cluster effects and the regressors. Thus we do the estimations by considering cluster-specific fixed effects, which allows for the possibility that the unobserved cluster effect in the error term $\varepsilon_{i,k,t}$ is correlated with the regressors (Woodbridge, 2002). Finally, we introduce Zellner's seemingly unrelated regression (SUR) estimation (see Zellner, 1962; Zellner & Huang, 1962) to estimate Eq. (7) for two time periods. On the one hand, SUR estimators are more efficient than those using OLS when the regression disturbances are correlated over time. On the other hand, SUR estimation can be used to test cross-equation constraints, enabling us to determine whether the estimated coefficients of the variables regarding H-O- and NEG-type interactions in the period of 2002–2009 are statistically different from the 1998–2001 coefficients.

4.2. Estimation results

We estimate Eq. (7) using SUR with cluster-specific fixed effects for two time periods, 1998–2001 and 2002–2009, respectively. Panel A in Table 6 reports the estimation results of Eq. (7) with area and industry dummies, and Panel B presents the results when all the area and industry characteristics are considered. The lower values of R^2 in Panel B regressions support the argument that the data on area and industry attributes introduced in our analysis is limited in explaining industrial comparative gain or loss in a city. In the discussions that follow we focus mainly on the Panel A regressions.

First, we find that the initial level of regional employment is always negative and highly significant, indicating the existence of mean reversion, and there is no statistically significant change in the size of the coefficient between 1998–2001 and 2002–2009.[9]

Then regarding factor supply variables, the SUR coefficients for the H-O-type interaction between local agricultural employment share Agrshare and industrial labor input intensity Labemp are both positive but only the former is statistically significant. For another H-O-type interaction between local agricultural employment share Agrshare and industrial labor wage share Labwage, the SUR coefficients for Agrshare × Labwage are positive in both of these two periods but not statistically significant. The Wald tests of cross-equation constraints show that neither of the coefficients of these two interaction variables in the period of 1998–2001 is different from their counterparts in the period of 2002–2009. The results for the coefficients on the full set of industry and area characteristics in Panel B are similar.

For NEG-type interaction variables, the coefficients on market access interaction with intermediate input intensity Maccess × Inter for the two time periods are positive but not statistically significant from zero. The coefficients for the market

[9] This result applies for a Wald test of the alternative hypothesis that the coefficient for 1998–2001 is equals to that for 2002–2009, that is, a one-sided test. We employ the same test for all other variables of interest in this analysis.

Table 6
SUR estimation with cluster-specific fixed effects: basic results.

	Panel A		Panel B	
	1998–2001	2002–2007	1998–2001	2002–2007
EMP (in logs)	−1.036***	−0.978***	−0.916***	−0.833***
	(0.034)	(0.033)	(0.031)	(0.031)
Agrshare × Labemp	0.017***	0.017	0.021***	0.021
	(0.006)	(0.020)	(0.006)	(0.021)
Agrshare × Labwage	0.008	0.095	0.010	−0.013
	(0.006)	(0.235)	(0.007)	(0.257)
Maccess (in logs) × Inter	0.003	0.002	−1.492	3.828
	(0.040)	(0.047)	(2.104)	(2.592)
Maccess (in logs) × Tech	0.001	0.017***	0.191	0.485
	(0.005)	(0.006)	(0.271)	(0.309)
Maccess (in logs) × Labspe	0.027***	0.031***	0.019***	0.025***
	(0.003)	(0.003)	(0.002)	(0.003)
Constant	2.513***	1.491	−42.065	54.823
	(0.923)	(1.411)	(28.871)	(36.632)
Location dummies	Yes	Yes		
Industry dummies	Yes	Yes		
Location characteristics			Yes	Yes
Industry characteristics			Yes	Yes
R^2	0.15	0.14	0.06	0.04
Number of observations	15,430	15,430	15,430	15,430

Dependent variable is industrial comparative gain or loss RGROWTH (to be more precise, if RGROWTH > 0, we take the logarithmic value of RGROWTH; if RGROWTH < 0, we take the negative logarithmic value of the absolute value of RGROWTH). Independent variables correspond to the beginning of the period for each panel. Standard errors are in parentheses. EMP is the initial level of regional employment of an industry. Agrshare and Maccess denote regional agricultural employment share and market access, respectively. Labemp, Labwage, Inter, Tech, and Labspe are labor input intensity, labor wage share, intermediate input intensity, technology intensity, and labor force specialization, respectively. ***,**,* denote statistical significance at 1% ,5%, and10% level, respectively.

access interaction with technology intensity Maccess × Tech are positive in both periods. In terms of their statistical significance, it is found that only the estimated coefficient on Maccess × Tech in the period of 2002–2009 is statistically different from zero, while that in the previous years is not. Regarding the third NEG-type interaction between local market access Maccess and industrial labor force specialization Labspe, the SUR coefficients on Maccess × Labspe are 0.027 (s.e. = 0.003) for 1998–2001 and 0.031 (s.e. = 0.003) for 2002–2007. Both of these coefficients are statistically significant at the 1% level. The Wald tests show that the coefficients for three NEG-type interaction variables in the period of 1998–2001 do not differ from their counterparts in the latter period except for the market access interaction with technology intensity Maccess × Tech. The results of the coefficients on

Table 7
SUR estimation with cluster-specific fixed effects: robustness check using alternative market access variables.

	Panel A		Panel B	
	1998–2001	2002–2009	1998–2001	2002–2009
EMP (in logs)	−1.037***	−0.979***	−0.984***	−0.887***
	(0.034)	(0.033)	(0.031)	(0.032)
Agrshare × Labemp	0.017***	0.017	0.020***	0.028
	(0.006)	(0.020)	(0.006)	(0.021)
Agrshare × Labwage	0.008	0.102	0.010	−0.158
	(0.006)	(0.235)	(0.007)	(0.259)
Maccess_G (in logs) × Inter	0.006	0.006	3.007*	7.380***
	(0.042)	(0.050)	(1.632)	(2.027)
Maccess_G (in logs) × Tech	0.001	0.019***	0.408*	0.840***
	(0.005)	(0.006)	(0.210)	(0.234)
Maccess_G (in logs) × Labspe	0.029***	0.033***	0.025***	0.030***
	(0.003)	(0.003)	(0.002)	(0.003)
Constant	1.210	−0.046	8.319	91.653***
	(0.998)	(1.461)	(21.286)	(27.233)
Location dummies	Yes	Yes		
Industry dummies	Yes	Yes		
Location characteristics			Yes	Yes
Industry characteristics			Yes	Yes
R^2	0.15	0.14	0.07	0.05
Number of observations	15,430	15,430	15,430	15,430

Dependent variable is industrial comparative gain or loss RGROWTH (To be more precise, if RGROWTH > 0, we take the logarithmic value of RGROWTH; if RGROWTH < 0, we take the negative logarithmic value of the absolute value of RGROWTH). Independent variables correspond to the beginning of the period for each panel. Standard errors in parentheses. EMP is the initial level of regional employment of an industry. Agrshare and Maccess_*G* denote regional agricultural employment share and market access, respectively. Labemp, Labwage, Inter, Tech, and Labspe are labor input intensity, labor wage share, intermediate input intensity, technology intensity, and labor force specialization, respectively. ***,**,* denote statistical significance at 1% ,5%, and10% level, respectively.

Table 8
SUR estimation with cluster-specific fixed effects: robustness check using samples with outliers excluded.

	Panel A		Panel B	
	1998–2001	2002–2009	1998–2001	2002–2009
EMP (in logs)	−0.997***	−1.038***	−0.911***	−0.908***
	(0.038)	(0.038)	(0.035)	(0.037)
Agrshare × Labemp	0.014**	0.014	0.019***	0.020
	(0.06)	(0.021)	(0.006)	(0.022)
Agrshare × Labwage	0.007	0.071	0.009	−0.044
	(0.006)	(0.244)	(0.006)	(0.265)
Maccess (in logs) × Inter	0.012	0.022	−2.735	4.985*
	(0.040)	(0.049)	(2.071)	(2.714)
Maccess (in logs) × Tech	0.0001	0.017**	−0.154	0.377
	(0.005)	(0.007)	(0.271)	(0.332)
Maccess (in logs) × Labspe	0.023***	0.030***	0.018***	0.022***
	(0.003)	(0.003)	(0.002)	(0.003)
Constant	1.523	1.326	−54.263	66.982*
	(1.068)	(1.567)	(28.500)	(38.497)
Location dummies	Yes	Yes		
Industry dummies	Yes	Yes		
Location characteristics			Yes	Yes
Industry characteristics			Yes	Yes
R^2	0.12	0.14	0.06	0.05
Number of observations	11,312	11,312	11,312	11,312

Dependent variable is industrial comparative gain or loss RGROWTH (to be more precise, if RGROWTH > 0, we take the logarithmic value of RGROWTH; if RGROWTH < 0, we take the negative logarithmic value of the absolute value of RGROWTH). Independent variables correspond to the beginning of the period for each panel. Standard errors are in parentheses. EMP is the initial level of regional employment of an industry. Agrshare and Maccess denote regional agricultural employment share and market access, respectively. Labemp, Labwage, Inter, Tech, and Labspe are labor input intensity, labor wage share, intermediate input intensity, technology intensity, and labor force specialization, respectively. ***,**,* denote statistical significance at 1% ,5%, and10% level, respectively.

NEG-type interaction variables in Panel B, where Eq. (7) is estimated with all the industry and area characteristics replacing area and industry dummies, are similar. Overall our results suggest that market access interaction variables were central to the location change of Chinese industries in both the pre- and post-WTO period.

We do several robustness checks. First, we examine the possibility that our results would hold when an alternative measure of market access is considered. We re-estimate Eq. (7) with a revised market-access variable, which is calculated based on trade gravity model as follows:

$$\text{Maccess\_G}_i = \sum\nolimits_{l \neq i}^{R} \text{GDP}_k / d_{il}, \tag{8}$$

where GDP_k is area k's total GDP in a particular year, and d_{il} is the spatial distance between city i and its trading partner l. Table 7 illustrates the estimation results using SUR with cluster-specific fixed effects. In all regressions, the results are similar to those in Table 6.

Secondly, one might also wonder whether the results are driven by outliers. We re-estimate Eq. (7) by dropping the samples in the highest and lowest quartiles of the distribution of regional comparative gains or losses of individual industries. Table 8 reports the estimation results when the samples in the 10% and 90% quartiles are excluded, respectively. In all cases, the results are similar to the results in Table 6.

4.3. Economic significance of the results

Following Klein and Crafts (2011) we calculate the standardized coefficients for all the interaction variables based on the SUR regressions in Panel A of Table 6.[10] These coefficients can provide a comparison of the relative importance of factor supply and market access in determining industrial comparative gain or loss in the number of workers for a city. We present the results in Table 9: Column (1) and (2) illustrate the standardized coefficients for five interaction variables in the periods 1998–2001 and 2002–2009, respectively.

As shown in Column (1), throughout the period 1998–2001 the H-O- and NEG-type forces jointly determined changes in the location of industries but the sum of the contributions of the former exceeds that of the latter. During the period of 2002–2009, it is found that the sum of contributions of NEG-type forces related to market access outweighs that of the H-O type forces (see Column (2)). This result may signify that entry into the WTO has allowed market access to play a more important role in explaining recent change of industrial location in China.

5. Conclusion

In this paper we analyze recent trends in intercity shifts in industrial employment in China, over a period that has coincided with China's entry into the WTO. First, we document redistribution patterns of industries across cities in China during both the

[10] To be specific, the standardized coefficient for each interaction variable is defined as the ratio of its standard deviation relative to that of dependent variable multiplying its estimated coefficient based on the regression results in Panel A of Table 6.

Table 9
Standardized coefficients of interaction variables.

	(1)	(2)
	1998–2001	2002–2007
Agrshare × Labemp	0.19	0.07
Agrshare × Labwage	0.01	0.01
Maccess (in logs) × Inter	0.00	0.00
Maccess (in logs) × Tech	0.00	0.04
Maccess (in logs) × Labspe	0.12	0.14

The standardized coefficient is defined as $\beta_i = \left[\frac{s(x_i)}{s(y)}\right] * b(x_i)$, where $b(x_i)$ and $s(x_i)$ are the estimated coefficient and standard deviation of one interaction variable, $s(x_i)$. $s(y)$ is the standard deviation of dependent variable, y. The standard coefficients are calculated from the SUR estimations in Panel A of Table 6. This table presents only the standardized coefficients of interaction variables.

pre- and post-WTO periods. It is found that all industries have experienced locational changes but the magnitudes of intercity shift vary across industries and over time. Labor-intensive industries are found to have experienced the largest shift before China's entry into the WTO in 2001 whereas high-tech industries are the largest shifters during the post-WTO period. The data also illustrates that the overall redistribution of industries has generally continued towards the coastal cities especially after China's entry into the WTO and despite inland shifts of some labor-intensive industries.

Second, we examined some of the mechanisms underpinning industrial relocation as suggested by the Heckscher–Ohlin (H-O) and New Economic Geography (NEG) theories and estimated whether their respective impacts have changed over the sample period. Our paper finds evidence of joint impacts of H-O- and NEG-type interactions between location and industry characteristics on recent changes in the location of industries in China, but with a relatively stronger impact of NEG-type forces regarding market access in the post-WTO period. The findings imply that entry to the WTO in 2001 has enabled market access to have a stronger impact on the location of industries in China. As such, local and national efforts to attract industrial development to certain areas are most likely to succeed by focusing on improving market access, for example, by improved transport linkages to large markets.

Appendix A

Appendix Table 1
Coastal cities: Industries with the 10 largest comparative gains and losses in the number of employees.

1998–2001			2002–2009		
Industry	Largest comparative gains	Type	Industry	Largest comparative gains	Type
Primary processing of raw fiber materials	89,909	Labor	Primary processing of raw fiber materials	337,312	Labor
Textile	64,025	Labor	Motor vehicle	186.447	Labor
Garment	63,031	Labor	Tile, lime and light building materials	97,072	Labor
Handcraft and arts	58,701	Labor	Transmission provisions and control equipment for electricity	80,593	High-tech
Electronic device	48,629	High-tech	Pump, valves and compressor	78,068	Labor
Leather products	48,315	Labor	Pressing and processing of steel	77,508	Labor
Ply wood	42,969	Resource	Electronic device	70,967	High-tech
Slaughtering and meat products	40,635	Resource	Electronic computer	69,899	High-tech
Knitted textile	38,610	Labor	Handcraft and arts	66,484	High-tech
Papermaking	35,491	Labor	Electric engine	62,976	High-tech
	Largest comparative losses			Largest comparative losses	
Motor vehicle	−56,299	Labor	Slaughtering and meat products	−29,601	Resource
Basic raw chemical materials	−53,554	Labor	Dairy products	−17,756	Labor
Heavy nonferrous metal smelting	−49,588	Labor	Medical equipment	−14,763	Labor
Cement, lime, and gypsum	−32,394	Labor	Leather products	−13,305	Labor
Pressing and processing of steel	−26,517	Labor	Wine	−11,252	Labor
Graphite and other non-metal products	−18,604	Labor	Broadcast and television equipment	−9,899	High-tech
Special equipment for metallurgy, mine and electric machinery	−14,806	Labor	Boat building	−9,598	Labor
Plastic film	−14,169	Labor	Other medical products	−7,665	Labor
Railway equipment	−14,443	Labor	Toys	−6,093	Labor
Wine	−14,330	Labor	Wood sawing and timber processing	−5,674	Resource

This table lists the 3-digit industries with the 10 largest comparative gains and losses for the coastal cities. In terms of TYPE, Labor, High-tech, and Resource indicate labor-intensive, high technology intensive and resource-oriented industries, respectively.

Please cite this article as: Bao, C., et al., Chinese manufacturing on the move: Factor supply or market access? *China Economic Review* (2012), http://dx.doi.org/10.1016/j.chieco.2012.08.005

Appendix Table 2
Central cities: Industries with the 10 largest comparative gains and losses in the number of employees.

1998–2001			2002–2009		
Industry	Largest comparative gains	Type	Industry	Largest comparative gains	Type
Motor vehicle	74,278	Labor	Chemical products for special usage	57,915	Labor
Steel making	47,214	Labor	Steel making	38,364	Labor
Basic raw chemical materials	31,135	Labor	Slaughtering and meat products	37,312	Resource
Graphite and other non-metal products	20,380	Labor	Chemical Fertilizer	32,004	Labor
Iron smelting	18,425	Labor	Manufacturing of cigarette	30,481	Resource
Railway equipment	16,943	Labor	Grain and forage processing	26,389	Resource
Fibrous fibers	14,545	Labor	Cement, lime, and gypsum	23,127	Labor
Boiler and motive power machinery	12,572	Labor	Dairy products	22,787	Labor
Ships	11,156	Labor	Boat building	19,011	Labor
Plastic film	10,487	Labor	Ply wood	18,743	Resource
	Largest comparative losses			Largest comparative losses	
Primary processing of raw fiber materials	−60,577	Labor	Motor vehicle	−185,211	Labor
Textile	−53,423	Labor	Primary processing of raw fiber materials	−109,786	Labor
Handcraft and arts	−47,407	High-tech	Pressing and processing of steel	−54,176	Labor
Garment	−41,774	Labor	Electronic device	−40,451	High-tech
Pressing and processing of steel	−39,447	Labor	Pump, valves and compressor	−28,113	Labor
Tile, lime and light building materials	−38,609	Labor	Battery	−23,671	High-tech
Knitted textile	−28,328	Labor	Metal products for construction	−23,344	Labor
Leather products	−27,974	Labor	Electric engine	−22,824	High-tech
Ply wood	−27,973	Labor	Special equipment for petro-chemistry and other industries	−22,823	High-tech
Electronic computer	−27,972	Labor	Fan, weighing apparatus and packing equipment	−22,822	High-tech

This table lists the 3-digit industries with the 10 largest comparative gains and losses for the central cities. In terms of TYPE, Labor, High-tech, and Resource indicate labor-intensive, high technology intensive and resource-oriented industries, respectively.

Appendix Table 3
Western cities: Industries with the 10 largest comparative gains and losses in the number of employees.

1998–2001			2002–2009		
Industry	Largest comparative gains	Type	Industry	Largest comparative gains	Type
Heavy nonferrous metal smelting	85,857	Labor	Motor vehicle	522,99	Labor
Cement, lime, and gypsum	555,13	Labor	Wine	43,818	Labor
Petroleum refining	33,092	Resource	Basic raw chemical materials	30,120	Labor
Sugar processing	30,925	Resource	Pressing and processing of steel	25,767	Labor
Special equipment for metallurgy, mine and electric machinery	27,514	Labor	Cement, lime, and gypsum	25,179	Labor
Wine	27,090	Labor	Leather products	25,098	Labor
Motorcycles	26,611	Labor	Slaughtering and meat products	20,728	Resource
Tile, lime and light building materials	24,523	Labor	Sugar processing	20,445	Resource
Basic raw chemical materials	22,804	Labor	Manufacturing of cigarette	15,887	Resource
Pressing and processing of steel	22,176	Labor	Processing of raw Chinese medical herbs and Chinese pharmaceutical	14,919	High-tech
	Largest comparative losses			Largest comparative losses	
Steel making	−28,670	Labor	Transmission provisions and control equipment for electricity	−63,860	High-tech
Electronic device	−26,220	High-tech	Primary processing of raw fiber materials	−39,879	Labor
Silk textile	−23,354	Labor	Communication equipment	−36,877	High-tech
Primary processing of raw fiber materials	−22,541	Labor	Electronic parts	−35,524	High-tech
Slaughtering and meat products	−22,211	Resource	Chemical products for special usage	−33,732	Labor
Papermaking	−19,020	Labor	General apparatus and meters	−22,092	High-tech

(continued on next page)

Appendix Table 3 (*continued*)

1998–2001			2002–2009		
Industry	Largest comparative losses	Type	Industry	Largest comparative losses	Type
Motor vehicle	−16,241	Labor	Electronic device	−21,897	High-tech
Garment	−15,947	Labor	Battery	−19,047	High-tech
Ply wood	−15,946	Labor	Tile, lime and light building materials	−19,046	High-tech
Handcraft and arts	−15,945	Labor	Special equipment for petro-chemistry and other industries	−19,045	High-tech

This table lists the 3-digit industries with the 10 largest comparative gains and losses for the western cities. In terms of TYPE, Labor, High-tech, and Resource indicate labor-intensive, high technology intensive and resource-oriented industries, respectively.

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