Has the "Flying Geese" Paradigm Occurred in China?

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Abstract: *In economic literature, the term "flying geese" refers to the movement of capital from developed regions to less developed ones. Using national data from above-scale manufacturing enterprises, this paper investigates whether the experience of "flying geese" has transpired in China for manufacturing industries. We find that, driven by the effects of agglomeration, prior to the mid-2000s, there had been an increasing concentration of industrial activities in the coastal regions. However, as labor and land costs increased, the manufacturing sector - especially the labor-intensive industries - began to relocate from the coastal to the interior regions.*

Keywords: *manufacturing industries, flying geese, industrial cluster*
JEL Classification: L60

1. Introduction

In the past three decades, the Chinese economy has experienced phenomenal growths in large part due to the rapid expansion in the labor-intensive manufacturing sector, which has been primarily concentrated in the coastal areas. In 2009, China's per capita GDP reached USD3,774, making China eligible for the status of a "middle-income country." As the economy develops, wages and other factor prices also tend to increase over time. Consequently, labor-intensive industries will eventually lose their traditional comparative advantage, pushing enterprises to move to other regions or countries with lower costs. Existing literature mainly focuses on the patterns of industrial relocation across countries: as factor prices go up in developed countries, the labor-intensive industries tend to move to other less expensive countries with the developed countries retaining only those capital-intensive, high value-added industries. In economic literature this pattern has been termed as the "flying geese model" (Okita, 1985; Kojima, 2000).

With China's opening up to the world beginning in the late 1970s, the coastal regions have enjoyed a geographic advantage compared to their interior counterparts because of their proximity to international markets. Chasing an abundant supply of cheap labor, massive foreign investment poured into the coastal regions. Coupled with favorable policy support from the central government, the coastal areas have witnessed over three decades of manufacturing boom. As a result, most of the manufacturing industries are clustered in the coastal regions (Lu, 2006; Long and Zhang, 2011). In just a few decades China became the "world's factory" and achieved a level of industrialization that took

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European countries more than two centuries to realize.

Although the booming manufacturing sector has generated ample employment opportunities, it also gradually exhausted the seemingly unlimited supply of labor. Since the early 2000s, there has been an increasing number of media reports on labor shortages, particularly in the coastal regions (Cai, 2010; Zhang et al., 2011). Since 2004, average wage has experienced double digit rate increases in many years of the period. There is a wide debate as to whether China has reached the “Lewis turning point”. Amidst the rising labor cost, the spatial distribution of industrial activities has begun to change.

For a long time, China had been a typical dual economy with a large supply of surplus labor in rural areas. As the burgeoning industrial sector drew millions of workers from their farms to manufacturing floors, the number of excess laborers in the rural areas dwindled. Consequently, workers began to find themselves with more leverage when negotiating wages with employers. At this stage, the wage rate is likely to climb at a much faster pace than previously, prompting debate on China’s status for the so-called “Lewis turning point.” After the turning point, the capital-labor ratio rises rapidly, exerting great pressure on labor-intensive enterprises. In order to survive in the new reality of labor shortage, they have to make a choice: to introduce more capital-intensive technologies to replace laborers, or to relocate the business to a region with lower labor costs.

In the long run, China will have to upgrade its industries by introducing more capital-intensive technologies and produce more high-quality goods. In the short run, however, because of large regional variations in factor prices, it is possible for enterprises to move their operations to interior regions to take advantage of the cheaper labor and land. Although some empirical studies (Fan, 2004; Luo et al., 2005) have shown that the relocation of business is actually from the interior to the coastal areas, these findings are likely due to the sample periods used, which are mostly up to the late 1990s or the early 2000s. By comparing the regional differences in labor cost from 2000 to 2007, Cai et al. (2009) demonstrated that it is economically viable to move labor-intensive industries to the interior regions. Using provincial-level data, Ruan and Zhang (2010) further confirmed that in the textile sector, the pattern of “flying geese” has in fact occurred. However, their findings are based on only one single sector and the aggregated data are derived solely from the provincial level. In this paper, we expand the analysis by Ruan and Zhang (2010) to the company level and to encompass all manufacturing industries. Our results show that since the mid-2000s, the proportion of assets located in inland regions in the manufacturing sector, especially in the labor-intensive industries, has steadily increased.

2. Descriptive Statistics

2.1 Sample Representativeness

Our study is based on the census data for above-scale manufacturing enterprises between 1998 and 2008 and covering 31 provinces and 30 two-digit manufacturing industries in China. All state-owned enterprises and non-state enterprises with annual sales income exceeding RMB500 million are included in the sample. The sample size ranges from about 100,000 in 1998 to about 300,000 in 2008. The dataset has a few unique features. First, it is a census survey for large-scale enterprises rather than a sampling survey. Second, the sample period encompasses the Lewis turning point around 2004 as shown in Cai (2007) and Zhang et al. (2011). The dataset has a deficiency in that it doesn’t cover private enterprises with sales less than RMB500 million. In order to understand the potential bias as a result of excluding the small firms, we compared the summary statistics drawn from our sample with those inferred from the China Economic Census in 2004 and 2008.

Table 1 presents the ratios of average asset, profit, and employment calculated from our sample relative to those computed from the economic census in 2004 and 2006 for major industries. Several features are apparent from the table. First, the difference is more significant for employment than for asset and profit. On average, our sample accounts for about two-thirds of the total employment compared to about 90% of the total asset and profit, in 2004. Second, the gap in employment between the two data sources narrowed in 2008. The ratio of employment covered in our sample to that in the economic census increased to 73%. Third, the difference in coverage varies greatly across industries. For example, the ratio for the recycling industry in 2004 was 0.45, suggesting that the sector is dominated by small enterprises. By contrast, almost all the tobacco enterprises are in the above-scale category as shown by the

Table 1: Comparing the National Above-scale Manufacturing Enterprise Survey with the Economic Census

Industry	Ratio (above-scale manufacturing enterprise / census manufacturing enterprise)						
	Asset		Profit		Employment		Main business
	2004	2008	2004	2008	2004	2008	2004
Agriculture food products	0.8349	0.8608	0.7439	0.8380	0.6279	0.6964	0.8867
Food products	0.8433	0.8662	0.8779	0.8659	0.6523	0.7117	0.8836
Beverages	0.8664	0.8896	0.9042	0.8969	0.6577	0.6880	0.8957
Tobacco products	1.0046	0.9989	0.9897	0.9990	0.9846	0.9645	1.0062
Textiles	0.8717	0.8870	0.8577	0.8662	0.7441	0.8104	0.8921
Wearing apparel	0.7913	0.8192	0.8932	0.8378	0.6586	0.7157	0.8558
Dressing and dyeing of furs	0.8268	0.8676	0.8481	0.8750	0.7332	0.8117	0.8854
Lumber	0.7118	0.7354	0.5469	0.6889	0.4559	0.5533	0.6926
Furniture	0.7194	0.7691	0.7092	0.6976	0.5637	0.6629	0.7738
Paper and paper products	0.8573	0.8961	0.8513	0.8610	0.6224	0.6959	0.8546
Publishing, printing	0.7261	0.7490	0.7964	0.7356	0.4818	0.5348	0.6959
Entertainment products	0.7958	0.8329	0.8562	0.7820	0.6987	0.7923	0.8553
Refined petroleum products	0.9693	0.9611	0.9709	1.0138	0.8416	0.9299	0.9877
Chemicals and chemical products	1.1044	0.9243	0.9347	0.9323	0.7132	0.7713	0.9270
Medical products	0.8999	0.9251	1.0404	0.9909	0.8355	0.9005	0.9717
Fibre products	0.9463	0.9536	0.9733	0.9504	0.8888	0.9292	0.9803
Rubber products	0.8812	0.9034	0.8772	0.8644	0.7100	0.7618	0.8881
Plastics products	0.7810	0.8114	0.7988	0.7923	0.5798	0.6593	0.8057
Non-metallic mineral products	0.8144	0.8211	0.6781	0.7449	0.4770	0.5346	0.7527
Basic metals	0.9706	0.9875	0.9834	0.9804	0.8873	0.9509	0.9811
Non-ferrous metals	0.9523		0.9764		0.8399		0.9614
Fabricated metal products	0.7677	0.7926	0.8235	0.7965	0.5866	0.6554	0.8176
General machinery and equipment	0.8348	0.8564	0.8500	0.8582	0.6322	0.6877	0.8318
Special machinery and equipment	0.8513	0.7768	0.9034	0.8491	0.6855	0.6281	0.8743
Transport equipment	0.9355	0.8804	0.9648	0.9180	0.7695	0.7652	0.9503
Electrical machinery and apparatus	0.8958	0.9186	0.9641	0.9492	0.7588	0.8447	0.9355
Computing machinery	0.9471	0.9106	1.0169	0.9381	0.8275	0.9230	0.9868
Precision and optical instruments	0.8526	0.8793	0.9795	0.9472	0.7087	0.7799	0.9150
Crafts	0.7534	0.6291	0.7127	0.6748	0.5987	0.5921	0.7778
Recycling	0.6722	0.7799	0.6492	0.7071	0.4539	0.6069	0.7796
All manufacturing	0.8988	0.8477	0.9062	0.8411	0.6758	0.7275	0.9084

Source: National above-scale manufacturing enterprise data (China National Bureau of Statistics); “The First Economic Census Bulletin” available from http://www.stats.gov.cn/zgjjpc/cgfb/t20051206_402294807.htm; “The Second Economic Census Bulletin” available from http://www.stats.gov.cn/was40/reldetail.jsp?docid=402610156.

Table 2: The Criterion of Labor-intensive Industries

International criterion		National criterion	
Industry Name	**CAPINT**	**Industry Name**	**Capital-labor ratio (1000 yuan per capita)**
Footwear, except rubber of plastic	0.443	Dressing and dyeing of furs	31.28
Wearing apparel, except footwear	0.481	Wearing apparel	37.01
Professional & scientific equipment	0.654	Entertainment products	37.23
Leather products	0.663	Crafts	46.18
Tobacco	0.73	Furniture	61.16
Printing and publishing	0.785	Electrical machinery and apparatus	78.64
Furniture, except metal	0.789	Lumber	86.27
Chemicals, other	0.800	Fabricated metal products	91.35
Other manufactured products	0.878	Textiles	91.68
Machinery, electric	0.924	Plastics products	94.33
Machinery, except electrical	1.017	Precision and optical instruments	94.36
Fabricated metal products	1.173	General machinery and equipment	110.24
Misc, petroleum and coal products	1.199	Recycling	110.51
Transport equipment	1.32	Special machinery and equipment	116.51
Food products	1.366	Computing machinery	116.56
Plastic products	1.416		

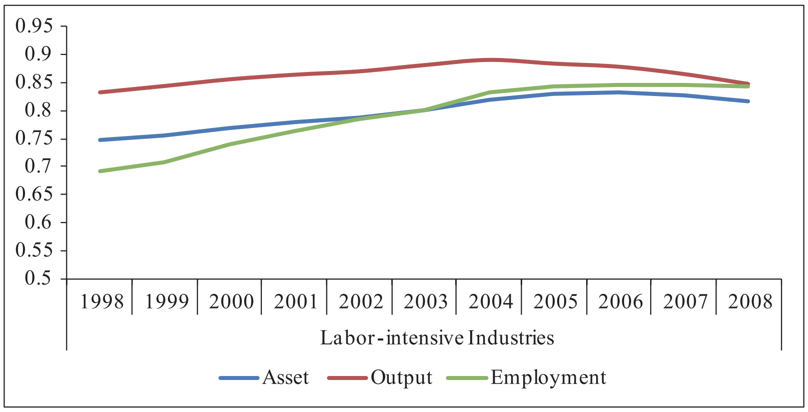
Notes: For the international criterion, see Ciccone, A. and E. Papaioannou (2009); the national criterion is based on the calculation using the above-scale manufacturing enterprise data of 2008.

greater ratios in asset, profit and employment which are close to 1. Overall, the sample has sufficient coverage in terms of asset and profit, but has less thorough coverage in employment.

2.2 The Spatial Distribution of Manufacturing and Labor-intensive Industries

Using the dataset for above-scale manufacturing enterprises, we examined the distribution of manufacturing industries in asset, profit, and output values during the period of 1998-2008 in inland and coastal regions. Particular attention is paid to labor-intensive industries. Although there is no universal definition, labor-intensive industries usually are those that use more labor relative to capital input during the production process. The capital-labor ratio may differ between developed and developing countries. In this paper, we selected a group of industries which displayed low capital-labor ratios in both China and the United States. Based on the dataset for above-scale manufacturing enterprises, we sorted the 30 manufacturing industries according to the value of the capital-labor ratio. The right column in Table 2 presents China's 15 most labor-intensive industries according to this measure, while the left column shows 16 industries with low capital intensity in the United States (obtained from Ciccone 2009). There are 12 overlapping industries between the two columns, which we categorize as labor-intensive industries: textile, garment, and footwear (18), leather products (19), wood processing (20), furniture (21), sporting goods (24), plastic products (30), fabricated metal products (34), general-purpose equipment (35), special equipment (36), instrumentation (39), communications equipment and computers (40), and electrical machinery and equipment (41).

Figure 1 displays the share of employment, asset and output values in the coastal regions spanning the period of 1998-2008 for the manufacturing sector as a whole (the left panel) and for only the labor-intensive industries (right panel).[1] The figure reveals a few interesting observations. First, the coastal region plays a dominant role in shaping China's manufacturing



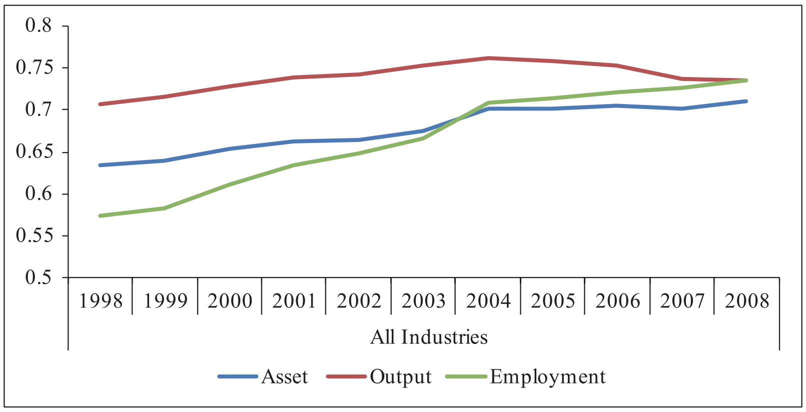


Figure 1: The Share of Manufacturing and Labor-intensive Industries in Coastal Areas

Note: Computed by the authors based on the national above-scale manufacturing enterprises survey.

sector. The region employed more than 55% of the workers, accumulated nearly two-thirds of the assets, and produced more than 70% of the output of the whole sector in 1998. By 2008, its proportions in employment, asset and output values had risen to all above 70%. Second, despite the increasing importance of coastal regions in the manufacturing sector during the sample period, the pace of growth has slowed down since 2004. In particular, the share of output has markedly decreased. Third, for the labor-intensive industries, since approximate the mid-2000s, the trend of capital flowing to the coast appears to have decelerated. In addition to the decline in the share of output, the share of assets in the coastal regions also exhibited a declining trend from 2006 to 2008, suggesting a capital outflow from the coastal to interior regions. The share of employment has leveled off since 2004. But because our sample encompasses only large firms, there is a possibility that it may fail to capture the movement in employment from the coastal to interior regions for vast numbers of small labor-intensive enterprises that tend to be more responsive to rising labor costs on the coast.

Next, we compare the return on asset (ROA) and per-capita profit in the two regions over time. As shown in Figure 2, initially ROA in the coastal region exceeds that in the interior region.

[1] The eastern (or coastal) region includes Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan; the interior (central and western) region comprises of Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan, Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang.

The gap is more evident for labor intensive industries. However, over time, regional difference disappeared. As a matter of fact, by the end of the sample period the interior region had slightly outperformed the coastal region in ROA. Per capita profit showed a similar trend. By 2008, despite an initial adverse business environment, the interior region had become a more lucrative destination for business. The coastal region's fortunes turned around in 2007 when the Asian financial crisis hit the area hard. Cai et al. (2009) also showed that the total factor productivity in inland areas increased faster than in coastal areas. The higher and continually rising ROA and profitability might have been be a key factor behind the recent relocation of business to the interior regions.

Rising labor cost might be another driving force behind the migration. Figure 3 shows the average labor cost in the two regions over the sample period. Overall, wages have steadily increased with growth accelerating since 2003. Moreover, laborers are more expensive in the coastal regions than in the inland regions. In 2007, an average coastal worker earned RMB29,000, RMB5,000 higher than his inland counterpart. Back in 1996, the average wage of coastal workers in the labor-intensive industries was less than the average wage of the entire manufacturing sector. However, by 2007 the wage difference across industries disappeared in the coastal regions while it continued to exist inland. This suggests that there is still some room for labor intensive industries to move inland to take advantage of the relatively lower labor costs.

As more enterprises move into interior regions, they will hire a greater number of local workers, consequently driving up local wages. As a result, the regional variations in wage rates are likely to decrease as businesses relocate from high-wage coastal regions to low-wage inland regions. To confirm this, we calculated a standard measure of inequality - the generalized entropy index (GE(0) index) - using wages at the firm level from the above-scale manufacturing dataset. The index dropped from 0.34 to 0.25 between 2000 and 2007,[2] suggesting a wage convergence over time. To examine how much of the variation is due to coastal-

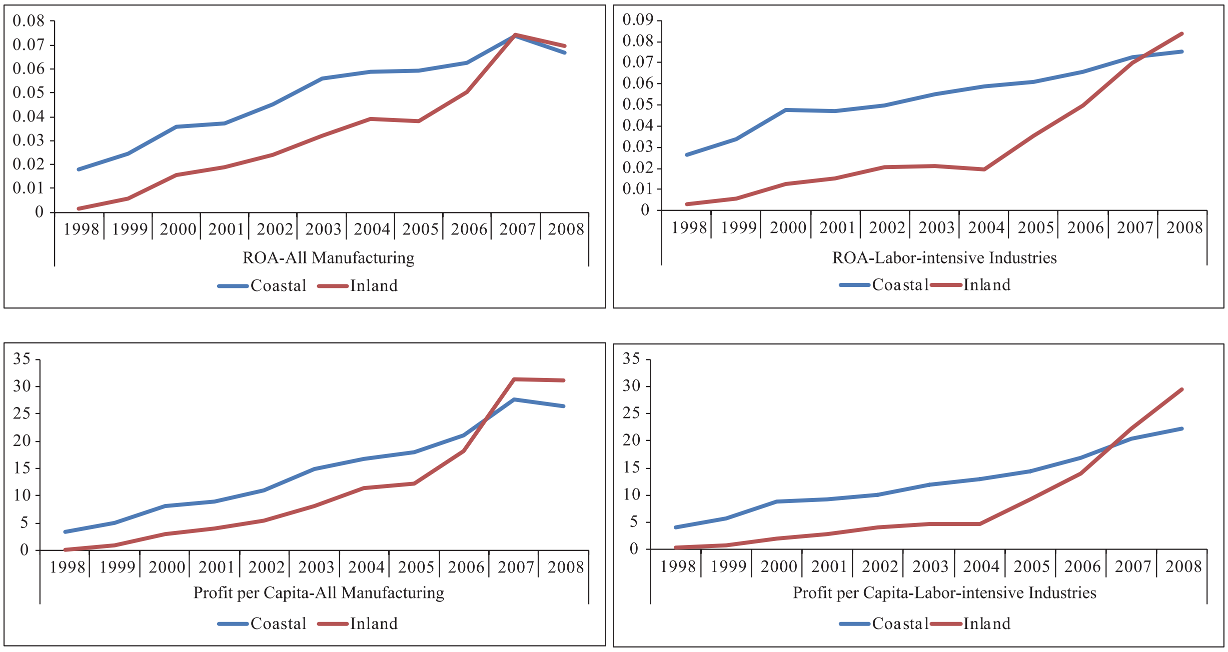


Figure 2: ROA and Profit Per Capita

Note: Computed by the authors based on the national above-scale manufacturing enterprises survey. ROA stands for return on asset.

inland differences, we further decomposed the overall GE(0) index into two components: the mean difference between the coastal and inland regions and within regional variation.[3] The share of coastal and inland differences in total wage variation declined from 0.058 to 0.029, indicating a narrowing wage gap between the inland and coastal regions. The trend in wage inequality appears to support the theory that the "geese" flocked to inland regions.

3. Quantitative Analyses on "Flying Geese"

After having presented evidence in support of the "flying geese" phenomenon, i.e., industrial relocations toward inland regions since the mid-2000s, next we conduct a quantitative analysis to examine the relative importance of various factors behind the shift in spatial distributions in manufacturing activities. In the literature, the term "flying geese" often refers to the movement of capital from a developed region to a less developed one. Following the convention, we present the results only for asset.[4] When firms select a location for investment, they often place the effects of agglomeration as their top priority. As stated by Marshall (1920) and Krugman (1991), agglomeration offers several key advantages, such as proximity to markets, easy flow of information and technology, and labor pooling. Assuming the other measures are the same, a region with a higher degree of agglomeration is likely to attract more business

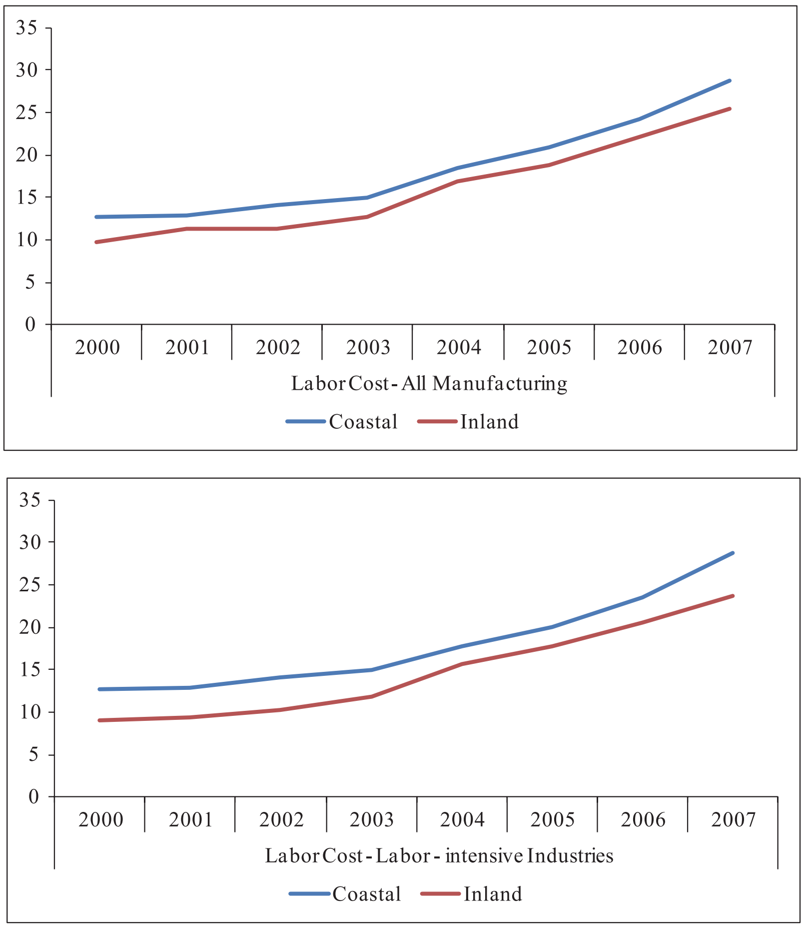


Figure 3: Labor Cost in Coastal and Inland Regions

Note: Computed by the authors based on the national above-scale manufacturing enterprises survey.

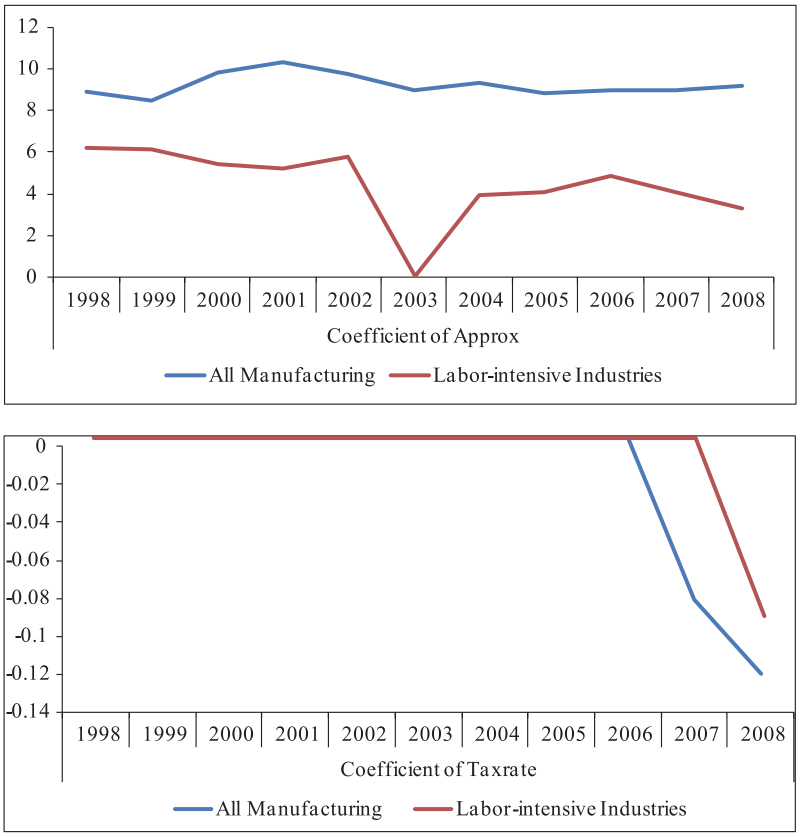


Figure 4: The Effect of Agglomeration and Tax Rate on Industrial Forming

Notes: Figure is based on the estimated results included in Table 3.

investment. So the first variable of interest is a measure of agglomeration. We use the proximity measure at the county level computed by Long and Zhang (2011) based on firm-level data from the China Industrial Census of 1995 as a measure of agglomeration.

However, as more firms cluster together and achieve high agglomeration, space becomes congested and the demand for land rises. Because the conversion of land from agricultural to non-farm use is strictly controlled by the government, the supply of land for industrial use can hardly keep pace with the rising demand. The combination of rising demand for, and limited supply of, land results in higher land price. This makes it harder for many firms to expand their production in the increasingly congested coastal regions. If firms want to expand their production base, they have to seek places with cheaper land, mostly in inland regions. Unfortunately, land price information at the county level is not available. As a compromise, we use local population data obtained from the China Population Census of 2000 as a proxy for land price.

The cost of living is generally higher in places where the land is more expensive. To attract workers, the coastal regions have to offer

[2] The data in 1998, 1999 and 2008 do not include wage information. Consequently, the sample period used in the calculation of the inequality measure is from 2000 to 2007.

[3] See Zhang and Kanbur (2001) for the application of the decomposition methodology.

[4] The results on output and employment are similar and available upon request.

better wages. Labor-intensive industries are particularly sensitive to labor cost. As labor cost increases, these firms are more likely to move elsewhere to obtain cheaper labor (Duranton & Puga, 2001; Diego & Anthony, 1996). Therefore, wage levels can be a major factor contributing to the relocation decisions of labor-intensive industries.

Although China has a unified tax code on paper, the effective tax rate differs greatly across regions (Zhang, 2006). This is largely due to China's centralized political system and decentralized economic system. In China, the size of local government is largely proportional to the registered population. However, under fiscal decentralization, local governments have had to raise most of their revenue to cover operational costs and provide local public goods and service. Naturally, regions with larger tax bases could afford to collect less tax revenue from individual enterprises than their less fortunate counterparts. In view of this, we also include the effective tax rate, ratio of collected taxes to gross industrial output, computed based on data from China Local Public Finance Yearbooks in the regression analyses.

To test the relative importance of the above four factors to the spatial asset distribution over time, we ran the following regressions year by year.

$$\ln(K)_{it} = \beta_1 \times approx_i + \beta_2 \times \ln(taxrate_i) + \beta_3 \times wage_{i,-1} + \beta_4 \times \ln(popu_i) + \beta_5 \times dummy_{province} + \varepsilon_i$$

In the above equation, i stands for county; K is total asset aggregated at the county level; *approx* is a measure of local agglomeration; *taxrate* represents the effective tax rate; $wage_{i,-1}$ refers to the average wage at the county level in the previous year. We used lagged wage data to

Table 3: Industrial Asset Formation (Cross-section Method)

	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008
All manufacturing											
Approx	8.88**	8.46**	9.80**	10.34**	9.73**	8.96**	9.32**	8.82**	8.99**	8.94**	9.16**
	(-1.66)	(-1.68)	(-1.61)	(-1.64)	(-1.6)	(-1.68)	(-1.43)	(-1.55)	(-1.43)	(-1.48)	(-1.51)
Population (ln)	1.25**	1.27**	1.28**	1.28**	1.21**	1.22**	1.15**	1.12**	1.08**	1.05**	1.04**
	(-0.06)	(-0.06)	(-0.06)	(-0.07)	(-0.07)	(-0.07)	(-0.06)	(-0.06)	(-0.06)	(-0.06)	(-0.06)
Taxrate (ln)	0.01	0.01	0.01	0.03	-0.03	-0.03	-0.03	-0.04	-0.06	-0.08*	-0.12**
	(-0.05)	(-0.05)	(-0.05)	(-0.05)	(-0.04)	(-0.04)	(-0.04)	(-0.04)	(-0.04)	(-0.04)	(-0.04)
r2_a	0.47	0.47	0.5	0.49	0.49	0.48	0.49	0.49	0.49	0.47	0.51
aic	5845	5902	5858	5913	6065	6121	6042	5979	5897	5850	5872
N	1660	1651	1682	1671	1706	1718	1728	1711	1702	1670	1716
Labor-intensive industries											
	1998	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**
Approx	6.21**	6.10**	5.45**	5.21**	5.81**	2.86	3.93**	4.06**	4.86**	4.07**	3.32*
	(-1.93)	(-1.99)	(-1.98)	(-2.03)	(-1.9)	(-1.94)	(-1.92	(-1.95)	(-1.84)	(-1.92)	(-1.85)
Population (ln)	1.14**	1.11**	1.16**	1.05**	1.00**	0.95**	1.05**	0.97**	0.93**	0.88**	0.92**
	(-0.08)	(-0.08)	(-0.08)	(-0.09)	(-0.09)	(-0.09)	(-0.09)	(-0.09)	(-0.09)	(-0.09)	(-0.08)
Taxrate (ln)	-0.05	-0.01	-0.03	-0.01	-0.04	-0.02	-0.01	-0.03	-0.06	-0.05	-0.09*
	(-0.06	(-0.06)	(-0.06)	(-0.06)	(-0.05)	(-0.05)	(-0.05)	(-0.05)	(-0.06)	(-0.06)	(-0.05)
r2_a	0.38	0.4	0.41	0.39	0.4	0.38	0.39	0.41	0.42	0.42	0.45
aic	5824	5583	5690	5517	5572	5493	5626	5561	5409	5263	5481
N	1482	1434	1468	1418	1431	1409	1431	1434	1422	1386	1470

Notes: The symbols **, and * represent significance level at 5%, and 10%, respectively. The t values are in parentheses.

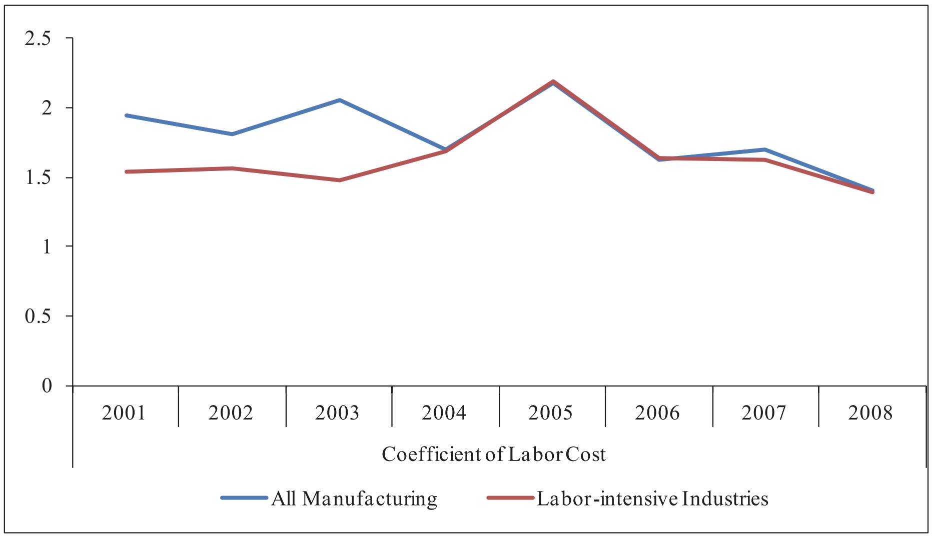


Figure 5: The Effect of Labor Cost on Asset Formation

Notes: Figure is based on the estimated results included in Table 3.

primarily reduce the potential reserve causality. We also included a set of provincial fixed effects ($dummy_{province}$) in the regressions.

Because data on wages are not available for 1998, 1999 and 2008, in the first set of regressions, we excluded the wage variable in the equation, thus the sample period still ranges from 1998 to 2008. The upper part of Table 3 presents the estimations for the entire manufacturing sector, while the lower panel restricts the sample to labor-intensive industries.

The coefficient for the agglomeration variable is consistently positive and significant throughout the years, suggesting that a county with a higher degree of agglomeration attracts more business investment. However, the significance of agglomeration effect on the whole manufacturing sector peaked at 10.34 in 2001 and has been in decline since then. Agglomeration commands a less important role in spurring asset accumulation for the labor-intensive industries than for the manufacturing sector as a whole. Interestingly, the significance of clustering in influencing spatial distribution of capital in the labor-intensive industries has declined more rapidly than the overall manufacturing industries as shown by the falling coefficient from 6.21 in 1998 to 3.32 in 2008.

With the exception of the last two years, the coefficient for the effective tax rate is generally insignificant for most years. The significant and negative coefficient in the last two years of the sample indicates that areas with lower effective tax rates have become increasingly popular for business investment.

In the next set of regressions, we included the wage variable. Due to missing values of wage data in 1998 and 1999, the sample period was reduced to 2000-2008. The estimated results are similar to Table 3 and are not reported here. Figure 5 only displays the coefficient for the wage variable from this new set of regressions. It is apparent from the figure that the coefficient first increased up to 2005 and has steadily declined since then. Prior to the 2000s, capital flocked to the coastal regions to take advantage of agglomeration despite a higher labor cost. The rising coefficient for the wage variable in the first half of the 2000s suggests that the positive agglomeration effect likely offset the rising labor cost. However, since 2005, county wage levels have become less correlated with local asset accumulation, suggesting that some firms have moved away from places with a high degree of clustering where workers often command higher wages to regions of lower wages.

The above year-by-year regressions are evidence that suggests capital first flowed from inland to coastal regions until the mid-2000s and subsequently the trend reversed afterwards. This approach has one deficiency in that it is not statistically efficient to estimate the regressions year by year. In addition, it does not directly test whether the share of asset possessed by the coastal regions had risen first before declining after controlling for the major determinants. To overcome these issues, we ran further regressions on the pooled samples as follows:

$$\begin{aligned}\ln(K)_{it} &= \beta_1 \times D + \beta_2 \times T \times D + \beta_3 \times T^2 \times D \\ &+ \beta_4 \times approx_i + \beta_5 \times T \times approx_i + \beta_6 \times T^2 \times approx_i \\ &+ \beta_7 \times \ln(taxrate_i) + \beta_8 \times T \times taxrate_i + \beta_9 \times T^2 \times taxrate_i \\ &+ \beta_{10} \times wage_{it-1} + \beta_{11} \times T \times wage_{it-1} + \beta_{12} \times T^2 \times wage_{it-1} \\ &+ yeareffect + \varepsilon_{it}\end{aligned}$$

In the above equation, *i* and *t* stand for

Table 4: Industrial Asset Formation (Panel Regressions)

	All manufacturing			Labor-intensive industries			Others		
	Model 1	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**
east	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
T*east	0.043**	0.085**	0.078**	0.140**	0.284**	0.258**	0.029**	0.068**	0.060**
	(-0.011)	(-0.03)	(-0.029)	(-0.013)	(-0.036)	(-0.036)	(-0.011)	(-0.031)	(-0.03)
T2*east	-0.003**	-0.006**	-0.005**	-0.009**	-0.020**	-0.017**	-0.002**	-0.005**	-0.004*
	(-0.001)	(-0.002)	(-0.002)	(-0.001)	(-0.003)	(-0.003)	(-0.001)	(-0.002)	(-0.002)
approx	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
T*approx	0.532**	0.236	0.241	-0.173	0.561	0.434	0.338*	0.464	0.324
	(-0.183)	(-0.481)	(-0.469)	(-0.246)	(-0.668)	(-0.662)	(-0.191)	(-0.508)	(-0.498)
T2*approx	-0.044**	-0.023	-0.019	-0.023	-0.075	-0.061	-0.012	-0.022	-0.007
	(-0.018)	(-0.037)	(-0.036)	(-0.024)	(-0.051)	(-0.05)	(-0.018)	(-0.039)	(-0.038)
Taxrate (ln)	-0.262	-0.415	-0.466	-1.023*	-1.393**	-1.634**	0.002	-0.032	-0.17
	(-0.482)	(-0.532)	(-0.532)	(-0.547)	(-0.61)	(-0.616)	(-0.495)	(-0.55)	(-0.552)
T*taxrate (ln)	-0.010**	0.007	0.005	0.003	0.001	-0.001	-0.007	0.003	0
	(-0.005)	(-0.012)	(-0.012)	(-0.006)	(-0.016)	(-0.016)	(-0.005)	(-0.013)	(-0.013)
T2*taxrate (ln)	-0.001*	-0.002**	-0.002**	-0.002**	-0.002	-0.002	-0.001**	-0.002*	-0.002
	(0)	(-0.001)	(-0.001)	(-0.001)	(-0.001)	(-0.001)	(0)	(-0.001)	(-0.001)
Wage (ln)			0.190**			-0.076			0.235**
			(-0.092)			(-0.102)			(-0.092)
T*wage (ln)			0.059*			0.111**			0.053*
			(-0.03)			(-0.034)			(-0.03)
T2*wage (ln)			-0.006**			-0.010**			-0.006**
			(-0.002)			(-0.003)			(-0.002)
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
r2_a	0.274	0.216	0.236	0.238	0.194	0.205	0.248	0.19	0.211
aic	44980	29991	28489	41467	27775	26464	46014	31002	29640
N	24131	17648	17495	19733	14227	13892	23988	17567	17410

Notes: The symbols**, and * represent significance level at 5%, and 10%, respectively. The t values are in parentheses; model 1 used the sample from1998-2008, model 2 and model 3 used the sample from 2001-2008. Variables of east and approx is dropped in the function because of multicollinearity with the year fixed effects.

county and year, respectively; T=year-1998; D is a dummy variable for the coastal region; *K* is total asset aggregated at the county level; approx is a measure of local agglomeration; *taxrate* represents the effective tax rate; and $wage_{i,-1}$ refers to the average wage at the county level in the previous year. Year fixed effects are also included. We combined the above variables with T and $wage_{i,-1}$ to capture the inverted-U shaped relationship between asset accumulation and several key determining factors as identified in Figures 4 and 5.

Table 4 reports separate regression results for the entire sample, including both labor-intensive industries and other industries. For each sample, we present three specifications. The first regression (R1), which excludes the wage variable, is based on the complete sample from 1998 to 2008. The third regression (R3) includes the wage variable. Due to missing values of the wage variable, the sample period is restricted to 2000-2008. In order to determine if any difference in the results between R1 and R3 is due to the additional wage variable or difference in the sample period, we repeated regression R1 on a smaller sample with a reduced period of 2000-2008.

The results for the coastal dummy variable and its interactions with T and are robust across all the specifications no matter which sample is used. Its interaction with the time variable is significant and positive across all the nine regressions, while its interaction with T^2 is consistently statistically negative in all the specifications. This shows that after controlling for clustering, wage level, and effective tax rate, the share of asset in the coastal regions exhibits a clear trend of first rising and subsequently declining. The results are consistent with the evidence as shown in the previous section.

The relationship between local wages and asset accumulation also follows an inverted-U shape. The coefficient for the interaction term of wage with T is statistically positive, while the interaction terms with the squared term is negative and significant. As time goes on, higher wages in the coastal regions would eventually push capital away. The results do not change whether we use the whole sample, the restricted sample composed of only labor-intensive industries, or the sample excluding the labor-intensive industries.

For the whole sample, the interaction term of effective tax rate with the squared term of T is significantly negative. This suggests that over time, effective tax rates become progressively more important in influencing asset accumulation in a location. When entrepreneurs select the destination of their investment, they have increasingly taken the business investment environment (lower taxes) into account. However, for labor-intensive industries, the results are not so vigorous. The coefficient for the interaction term of effective tax rate with T^2 is significantly negative only in the first regression on the sample over the period of 1998-2008. It loses significance when the sample period is cut to 2000-2008.

4. Conclusions

In the past several years, there have been increasing media reports on labor shortages, in particular in the coastal regions. Some have argued that China has passed the Lewis turning point (Cai, 2008; Zhang et al., 2011). As labor cost continues to rise, the labor-intensive manufacturing industries, most of which are located in the coastal regions, will gradually lose their cost advantages in the international market. They will either have to improve their quality to move up the value chain or relocate their businesses to locales with lower labor costs.

Based on the census-type survey for above-scale manufacturing enterprises from 1998 to 2008, this paper shows that the migration of capital from the coastal to the inland regions has been happening since the mid-2000s, which precisely corresponds to the timing of the Lewis turning point. As investment flocked inward, wage rates in the interior region caught up with those on the coast. Consequently, the regional differences in wages have narrowed over time. As China is a large country with huge regional differences, it may take many years for wages to equalize across regions. The "geese" won't stop flying inward until that date. After that, there is likely going to be massive relocations of labor-intensive industries from China to other developing countries with cheaper labor, such as Bangladesh and Ethiopia. However, it is not clear when that day will occur.

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