Industrial Agglomeration of Chinese Food Processing

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Abstract

Food processing has been widely recognized as a traditional, unskilled-labor intensive production. Yet rapid development in technology drives food processing into more technology-oriented industry. This paper utilizes a fixed effects model to test the hypothesis that the food processing industry is a high technology industry. The research employs a unique natural experiment where some provincial governments in China liberalized migration policies for highly educated/highly skilled (HEHS) workers. Theory holds that such labor liberalization policies will increase the level of industrial agglomeration by high technology firms facing a shortage of talent. The data are the 2001-2010 3-digit industrial and provincial level employment data from the China Labor Statistical Yearbook. This paper found strong evidence that the HEHS labor pool affected the location decision of food processing firms in China. The result supports recent literature that the food and agribusiness sector is increasingly dependent on knowledge workers and high technology. Other traditional determinants for industrial agglomeration: scale economies and proximity to markets are also found to promote industrial agglomeration in the food processing industry.

Key words: food processing, China, industrial agglomeration, high-educated/high-skilled labor, migration, fixed effects model

I. Introduction

One of the most important trends in the world food and agribusiness in recent decades has been the acceleration of technology-oriented innovation (Rademakers, 2012). The next generation of innovators needs to invest in science, technology, engineering and math as the agricultural becomes increasingly sophisticated (Grant, 2012).

Yet it has been widely recognized that agriculture is a traditional profession, and agribusinesses may resist innovation and be slow to change (Shelman and Connolly, 2012). High tech industries recruit scientists, engineers, and technicians at least twice the average for all industries (Hecker, 2005), yet food processing, for example, employs high technology talent at only 90% of the average of all industries (Table 1). Thus there is an empirical question whether food and agribusiness is a high technology sector. One practical implication of being high versus low tech concerns a fierce competition for talent, where traditional high technology industries often outbid food and agribusiness, which is often thought of as labor intensive and an employer only of low or unskilled employees (Duerksen, 2012).

(Insert Table 1 here)

This paper employs a natural experiment to test if food processing is high or low tech. Specifically the empirical analysis measures whether access to high-educated/high-skilled (HEHS) labor pool positively influences food processing firms' location decisions. Theory posits that high technology industries will agglomerate when HEHS labor pools become available. The rest of the paper proceeds as follows: section II contains a literature review; section III presents the method and data; and section IV describes the results and conclusions.

II. Literature Review

Industrial agglomeration, initially proposed by Alfred Marshall, refers to the advantages that firms producing similar goods can attain by co-location (Fujita, 2002).

Agglomeration provides a source of sustainable competitive advantage for a regional economy (Chinitz et al., 1961; Porter et al., 2002). However, an essential condition for industrial agglomeration, free flow of labor, is restricted in China as each local government seeks to protect its industrial base. These local policies may limit the natural formation of industrial agglomeration and as a result make the incumbent firms and the region less competitive (Young, 2000). The lack of competitiveness leads to higher local prices, poorer quality, reduced innovation, or vulnerability to import substitution.

Accessibility to human skill abundance plays a crucial role in firms' location decisions (Basdas, 2009). Pools of high skilled labor will attract investment by technology-oriented industries. High technology labor pools provide not only supply-based economies, but positive externalities result from knowledge spillovers among firms and the free flowing labor pool (Baptista and Swann, 1998). But regionally based policymaking in China restricts high-educated/high-skilled (HEHS) labor migration (Fan, et. al, 2009). Limited HEHS labor mobility reduces the knowledge transmission from labor to firms and among firms, and therefore hinders the formation of industrial agglomerations.

On one hand, rapid development in technology and globalization drives contemporary food and agribusinesses to be more sophisticated and dynamic (Shelman and Connolly, 2012). As a result, significant investment in science, technology, and engineering result (Grant, 2012). Companies in the global food and agribusiness need talented people to solve the important challenges posed by scarce resources such as food, energy and water (Rademakers, 2012). The expectation to produce more to meet the world's growing demand, while simultaneously reducing the impact on the natural environment requires high levels of talent (Goldsmith, 2010; Shelman and Connolly, 2012). The talent shortage is broadening and deepening in food and agribusiness as it becomes more technically complex (Lyons and Connolly, 2012; Duerksen, 2012).

On the other hand, however, the food industry often makes location decisions based on natural endowments, input abundance, increasing returns to scale, and low transport costs; not HEHS labor pools. Food processing for example depends on abundant agriculturally produced raw materials and orients its location decisions accordingly (Deichmann et al., 2005). Increasing returns to scale is a significant force behind agglomeration in food and beverage industry (Yilmazkuday, 2011). Low transportation costs complement scale economies thus provide an additional driver of location in food manufacturing (Davis and Schluter, 2008).

China experienced a transition from a central planned economy to a market economy in 1978. The State Council launched reform on labor mobility by gradually allowing interregional migration since 1984. The "Talent Residence Permit" (TRP) is a special migration reform targeting the location decision of HEHS workers in order to improve knowledge spillover effects and comparative competitiveness in a region. TRP policies entitle engineers, technicians, scientists, managers and other employees with college degrees or in-depth knowledge of science and technology to be eligible for permanent residency in selected cities. As of 2010, Fujian (2002), Shanghai (2002), Beijing (2003), Guangdong (2003), Jiangxi (2003), Liaoning (2003), Hunan (2004), Shandong (2004), Shanxi (2004), Zhejiang (2004), Jilin (2005), Sichuan (2005), Nei Mongol (2006) and Shaanxi (2006) implemented TRP policies (Figure 1).

(Insert Figure 1 here)

The research tests the causal forces behind agglomeration or the lack of agglomeration of food processing. In doing so we test the hypothesis that HEHS labor mobility liberalization positively affects food processing industrial agglomeration. The research employs a set of natural experiments to estimate the response of the industrial agglomeration when liberalizing HEHS migration. This study improves the previous literature in three ways. First, this research focuses on a particular migration policy-the Talent Residence Permit (TRP)-to estimate the response of the industrial agglomeration outcome in food processing. Second, this research extends previous work by examining the effect of labor liberalization across the entire nation (thirty one provinces). Third, this study differentiates HEHS specific labor liberalization policy with the overall labor mobility policy.

III. Method and Data

The employment location quotient is commonly employed to measure regional industrial agglomeration (Holmes and Stevens, 2002). It compares "the relative concentration of industry employment in a given location with the relative concentration of industry employment in the nation (Holmes and Stevens, 2002, page 683)." The location quotient is defined as

(1) $\mathrm{LQ_{ij}} = \frac{\frac{\mathrm{e_{ij}}}{e_j}}{\frac{\mathrm{E_i}}{\mathrm{E}}}$ where: $\mathrm{e_{ij}}$ is employment in industry i in province j; $\mathrm{e_j}$ is total local employment in province j; $\mathrm{E_i}$ is employment in industry i in the nation; E is total employment in the nation. LQ is equal to 1 when the percentage of employment within a particular industry in a local area is equal to the national average percentage of employment (Donoghue and Gleave, 2007). If the LQ is over 1, then the industry is "over representative" in the region and is likely to constitute agglomeration since the industry has an above average concentration of employment (Donoghue and Gleave, 2007).

This study employs a fixed effects model to portray the effects of skilled labor liberalization expansion on food processing industrial agglomeration. The setting is similar to that examined by Gruber and Yelowitz (1999) and Yelowitz (1995), who study Medicaid expansion in United States. Their identification strategy comes from the fact that the expansion of Medicaid occurred at a differential pace across the various states in the United States. Similarly, several provinces in China implemented TRP policies at different times.

The TRP policy variable varies by province, which is a more aggregate level that is common with panel data sets. There may be omitted variable bias that is unobserved at the province and year level (see Angrist and Pischke, 2008). To address the omitted variable bias we employ a difference in differences approach that utilizes assumptions for the control provinces.

First we assume that in the absence of the TRP policy, the location quotient is determined by the sum of a time-invariant province effect and a year effect that is common across provinces (Equation 2).

(2) $E(LQ_{0ijt}|j,t) = \gamma_j + \mu_t$

Following Angrist and Pischke (2008), i indexes industry, j denotes province, t denotes year, LQ_{0ijt} means the potential outcome when there is no TRP policy.

Let $Policy_{jt}$ be a dummy for TRP provinces, where provinces are indexed by j and observed in time t. $LQ_{1ijt} - LQ_{0ijt}$ measures the difference in potential outcome with TRP policy versus outcome without the TRP policy. The second assumption is that the slope of the change in location quotient would be the same in policy and non-policy provinces in the absence of TRP policy.

(3) $E(LQ_{1ijt} - LQ_{0ijt}|j,t) = \beta$, we have $LQ_{ijt} = \gamma_j + \mu_t + \beta Policy_{jt} + \varepsilon_{ijt}$

(4) $E(\varepsilon_{ijt}|j,t) = 0$

Using Angrist and Pischke's (2008) format we hypothesize that the TRP policy will change the slope of the rate of agglomeration in food processing (Equation 3). It is assumed that the error term is independent of the unobserved province and year effects (Equation 4).

The two fitted location quotient curves represent similar shapes before 2006. We hypothesize the steeper slope after 2006 is the result of a freer flow of HEHS talent (Figure 2).

(Insert Figure 2 here)

The treatment group is defined as the food processing industry in liberalizing provinces. The control group includes the food processing industry in non-policy provinces (Table 2).

(5) $Policy_{jt} = 1(\text{j} = \text{TRP province}) * 1(\text{t} \geq \text{effective year})$;

where j indexes the province, t indexes the year.

(Insert Table 2 here)

Following Gruber and Yelowitz (1999) in a similar fashion, the fixed effect regression models is as follows:

(6) $$\mathrm{LQ_{ijt}} = \beta_0 + \beta_1 1(\mathrm{j = TRP\ province}) * 1(\mathrm{t} \geq \mathrm{effective\ year}) + \beta_2 \mathrm{TIME_t} + \beta_3 \mathrm{PROV_j} + \beta_4 \mathrm{X_{ijt}} + \varepsilon_{\mathrm{ijt}}$$

where j indexes the province and t indexes the year. $\mathrm{LQ_{ijt}}$ is the dependent variable for industrial agglomeration, measured as location quotient. The term $\mathrm{X_{ijt}}$ is a vector of variables controlling for the traditional determinants for industrial agglomerations; including vertical disintegration, scale economy, and proximity to markets (see Krugman and Venables, 1996; Ellison and Glaeser, 1999). $\mathrm{PRO_j}$ is a full set of province dummies, and $\mathrm{TIME_t}$ is a full set of time dummies.

The parameter β_1 captures the variation in the dependent variables specific to the food processing industry in policy provinces relative to non-policy provinces (Kim, 2013). The β_1 provide estimates of the effect of the TRP policy on certain provinces directly targeting HEHS talent. Therefore, the TRP effect is captured by comparing the difference between food processing industrial agglomeration in policy provinces versus non-policy provinces. The relationship is represented by (Kim, 2013):

(7) $$\beta_1 = \{\mathrm{E}[\mathrm{LQ_{ijt}} | \mathrm{X}, \mathrm{policy_{jt}} = 1]\} - \{\mathrm{E}[\mathrm{LQ_{ijt}} | \mathrm{X}, \mathrm{policy_{jt}} = 0]\}$$

X includes all of the other covariates and the fixed effects.

Data

This study uses two sets of China's provincial 3-digit industrial statistics as the basic statistical data. One is China Labor Statistical Yearbook from 2001-2010 and the other is China Industry Economy Statistical Yearbook from 2001-2010. There is reasonable comparability between both data sets. Both of them are collected at the 3-digit industry level from the Annual Survey conducted by China's National Bureau of Statistics for the period 2001-2010. These two data sets are complementary. The China Labor Statistical Yearbook does not include information like industry output, industry sales and operating costs, while the China Industry Economy Statistical Yearbook includes such information. The China Labor Statistical Yearbook collects employment for thirty 3-digit manufacturing industries for 31 provinces.

Unfortunately not all data exists for all industries across all provinces and years. All dependent variables and treatment data exist, but control variables are missing for ten industries. These industries were dropped. The lack of data reduces the number of data points from 9,300 to 6,200. Of these 6,200 data points, 14.8% were imputed due to missing values (Appendix 1).

Vertical Disintegration

The availability of specialized inputs leads to the geographic concentration of downstream firms (Fujita, 2002; Marshall, 1920; Lu and Tao, 2009). Firms can obtain inputs from specialized suppliers rather than making them within an integrated plant where they become more vertically integrated (Holmes, 1999). Following Holmes (1999) vertical disintegration measures the ratio of purchased inputs to the value of outputs (Equation 8). Therefore we hypothesize that firms that purchase a high percentage of their inputs (vertically disintegrated firms) will be more input focused relative to HEHS labor inputs. The vertical disintegration coefficient serves to validate the TRP policy driver of agglomeration. For example, ceteris paribus a vertically disintegrated firm's location decision could be more influenced by access to supplier markets rather than access to HEHS labor pool. Firms with high cost of goods sold, such as food firms that depend on commodity inputs, will not co-locate. Thus the greater the disintegration the lower the location quotient, and the expected sign will be negative.

$$(8)\ \text{vertical disintegration} = \frac{\text{purchased inputs incuding raw materials}_{ij}}{\text{total output}_{ij}}$$

Scale Economies

Scale economies also positively relate to industrial agglomeration (Krugman and Venables, 1996; Holmes and Stevens, 2002). Following (Lu and Tao, 2009), this study constructs an average firm size variable that is defined as the total output of an industry divided by the number of firms in the industry (Equation 9). The scale economy coefficient is expected to be positive.

$$(9)\text{scale economy} = \frac{\text{total output of the industry}_{\text{ij}}}{\text{number of firms in the industry}_{\text{ij}}}$$

Proximity

Firms also locate closer to customers in order to reduce transportation costs and improve their marketing efficiency (Ellison and Glaeser, 1999). Following Ellison and Glaeser (1999), this study constructs a "proximity" variable to capture the idea that firms will reduce transport costs or improve marketing by locating closer to customers (Equation 10). The higher value of "proximity" indicates lower transport costs, and a higher level of industrial agglomeration. "Proximity" is expected to positively relate to the location quotient.

$$(10)\ \text{Proximity} = \frac{\text{industry}_{\text{ij}}\ \text{sales}}{\text{total industry}_{\text{i}}\ \text{sales}} * \text{population density}_{\text{j}}$$

where i indexes the industry, j indexes the province.

In sum the model includes three control variables, Vertical Disintegration, Scale Economy, and Proximity. There are also two unobserved variables, year and province effects. Finally the TRP implementation is the one treatment variable. The three control variables and one treatment variable have significant but minor levels of correlation (Table 3)

(Insert Table 3 here.)

There are 20 industries after deleted industries with excessive missing data. For comparative purposes we compare Food Processing with: 1) a typical high tech industry, as measured by high levels of R&D employment, Measurement Instrument Manufacturing; and 2) all 20 of the manufacturing sectors (Table 4). The R&D intensity of Measurement Instrument Manufacturing is five times that of food processing and two thirds large than the average for all 20 industrial sectors.

(Insert Table 4 here)

IV. Results and Conclusions

The fixed effect model examines the effects of TRP policy on food processing industrial agglomeration. The null hypothesis is confirmed that the TRP policy is positively correlated with agglomeration reflecting the high technology nature of food processing (Table 5). Food processing firms do respond to the availability of HEHS labor pools and co-locate in order to access talent. Also as hypothesized, the location quotient of the Instrument Manufacturing industry too is positively affected by the TRP policy implementation. All Manufacturing is not.

(Insert Table 5 here.)

When Food Processing firms purchase high levels of inputs; thus when more disintegrated, they have a lower location quotient. This is consistent with expectations. Thus there is a statistically significant disintegration affect reducing agglomeration in Food Processing. The coefficient for Instrument Manufacturing and All Manufacturing are negative but not significant.

Increasing returns and greater scale economy leads to greater industrial agglomeration. As expected, the scale economy effects are positive for all three industry classes but only significant for Instrument Manufacturing and All Manufacturing.

Finally the proximity coefficient is negative but insignificant for Food Processing. Being closer to high population centers is hypothesized to lead to greater agglomeration. This relationship does not hold for Instrument Manufacturing, but does hold for All Manufacturing.

The provincial unobservable variables are quite powerful in the model (Table 6). Of the 31 provinces, 24 of the dummy coefficient values were significant at the .10 level when compared to province #1; with 20 being positive and four being negative. The interpretation is that provincial policies significantly affect the location clustering of food processing firms relative to province #1. On the other hand, the year effects on the model are minimal, though significant in seven of the nine years when compared to 2001, the base year. The signs on the year dummies are all negative. Thus ceteris paribus, agglomeration trends for Food Processing were negative, albeit quite modest.

Fan et al. (2009) raise an important finding that permits are more easily granted in software, biotech and digital manufacturing in coastal cities where there are shortages of HEHS workers. The finding challenges our model's assumption as to the independence of the TRP policy implementation at the provincial level for Food Processing. The actual HEHS labor numbers by industry within each province would make for a superior regressor when compared to the provincial TRP policy dummy that we use. Using the actual HEHS data would allow the identification of specific industries that do or do not receive the treatment. Unfortunately those data do not exist so must employ the TRP dummy.

Intuitively bias may be present in our model because HEHS dependent industries logically might lobby to impose the TRP policy. But the TRP policies are part of the overall Chinese economic reform from planned economy towards market economy. Since the 1980's, China launched economic reforms by releasing segments of the economy from central control (Young, 2000). There have been many calls to change the inherent distortion policies including the labor market by gradually allowing rural-urban and interregional migration (Security, 1985). TRP is a special migration reform encouraging HEHS mobility liberalization. The TRP policies are identified as part of social reform and not an industry-based strategy. Therefore, while the TRP may benefit only some industries, the policy is part of a larger plan to allow the freer flow of labor. Thus an endogenous lobby effort by HEHS industry is likely not the driver to TRP implementation.

Finally, we worry about the direction of causality. Some provinces, like Jiangxi, Hunan, Shaanxi, duplicate the policies in coastal provinces in order to catalyze local industrial agglomeration (Zhang, 2009). Therefore, the TRP implementation is a strategy to facilitate the formation of high-tech industrial agglomeration, not the result of it. We employ the Granger test for causality to check whether past implementation of the TRP affects the future location quotient while future TRP implementation does not lead to higher location quotients in previous years. Following Autor (2003), Angrist and Pischke (2008), we add "lagging" policy dummies, which occur before the TRP adoption; and "leading" policy dummies, which occur after the TRP adoption (Autor 2003). As shown in Equation 11, m= 4 and q = 1, where m reflects four periods before TRP adoption, and q reflects the one period after TRP adoption. Thus there are five TRP policy implementation dummies beginning four years in the past, the current period, and one period in the future.

(11) $$\mathrm{LQ}_{\mathrm{ijt}} = \mathrm{LQ}_{\mathrm{jt}} = \beta_0 + \sum_{\tau=0}^{m} \beta_{-\tau}\mathrm{Policy}_{\mathrm{j,t-\tau}} + \sum_{\tau=1}^{q} \beta_{+\tau}\mathrm{Policy}_{\mathrm{j,t+\tau}} + \beta_3\mathrm{TIME}_{\mathrm{t}} + \beta_4\mathrm{PROV}_{\mathrm{j}} + \beta_5\mathrm{x}_{\mathrm{jt}} + \varepsilon_{\mathrm{ijt}}$$

The estimation results support the hypothesis as to the direction of causality. The results show no effect that is significant in one year prior, a sharp response in year zero, and no effect in the next two years (Figure 3).

Finally there are some limitations to our analysis. First, the data are aggregated at the provincial and industrial level. Firm level data, would be much preferred. Second, there are two drawbacks using the location quotient to measure industrial agglomeration. On the one hand, it fails to determine whether or not a location with a concentration of employment corresponds to a particular industry (Donoghue and Gleave, 2007). A proper identification strategy would segment the manufacturing industries in terms of their need for HEHS labor. It is possible to identify industries that are affected by this TRP policy and which are not using the information about HEHS migrant employment inflow and outflow. On the other hand, the location quotient also utilizes ratios so does not employ the absolute size of local industry's employment (Donoghue and Gleave, 2007).

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Table 1 R&D Intensity on Manufacturing Industries (2010)

Industry	R&D Intensity	R&D Intensity Relative to Average	Category
1 Processing of Food from Agricultural Products	1.08%	94.74%	Low-tech
2 Manufacture of Foods	1.33%	116.91%	Low-tech
3 Manufacture of Beverage	1.65%	144.92%	Low-tech
4 Manufacture of Tobacco	1.98%	174.05%	Low-tech
5 Manufacture of Textile	1.43%	125.85%	Low-tech
6 Manufacture of Textile Wearing, Apparel, Foot-ware and Caps	0.37%	32.14%	Low-tech
7 Manufacture of Leather, Fur, Feather and Its Products	0.53%	46.18%	Low-tech
8 Processing of limbers, Manufacture of Wood, Bamboo, Rattan, Palm and Straw Products	0.49%	43.22%	Low-tech
9 Manufacture of Furniture	0.62%	54.69%	Low-tech
10 Manufacture of Paper and Paper Products	1.46%	128.30%	Low-tech
11 Printing, Reproduction of Recording Media	1.30%	113.78%	Low-tech
12 Manufacture of Articles for Culture, Education and Sport Activities	0.81%	70.88%	Low-tech
13 Processing of Petroleum, Coking, Processing of Nuclear Fuel	2.05%	180.09%	Low-tech
14 Manufacture of Chemical Raw Material and Chemical Products	3.45%	302.78%	High-tech
15 Manufacture of Medicines	5.48%	481.54%	High-tech
16 Manufacture of Chemical Fiber	5.21%	457.21%	High-tech
17 Manufacture of Rubber	3.18%	279.69%	High-tech
18 Manufacture of Plastic	2.60%	228.09%	High-tech
19 Manufacture of Non-metallic Mineral Products	1.58%	138.82%	Low-tech
20 Manufacture and Processing of Ferrous Metals	3.47%	305.06%	High-tech
21 Manufacture and processing of Non-ferrous Metals	3.06%	268.80%	High-tech
22 Manufacture of Metal Products	2.34%	205.51%	High-tech
23 Manufacture of General Purpose Machinery	4.56%	400.69%	High-tech
24 Manufacture of Special Purpose Machinery	4.72%	414.58%	High-tech
25 Manufacture of Transport Equipment	5.41%	475.61%	High-tech
26 Manufacture of Electrical Machinery and Equipment	5.95%	522.43%	High-tech
27 Manufacture of Communication Equipment, Computer and Other Electronic Equipment	7.78%	683.69%	High-tech
28 Manufacture of Measuring Instrument and Machinery for Cultural Activity and Office Work	4.58%	402.69%	High-tech

Source: author's calculation of China Labor Statistical Yearbook, China Industry Economy Statistical Yearbook

Table 2 Treatment Dummies Summary

	2001-2004		2005-2010	
Province	Education/Skill Limit	$Policy_{jt}$	Education/Skill Limit	$Policy_{jt}$
Beijing	College degree or above/ Intermediate technician Certificate	1		6
Tianjin		0		0
Hebei		0		0
Shanxi		0	College degree or above/ 2-year Managerial experience	6
Inner Mongolia		0	College degree or above	4
Liaoning	Professional Certificate	3		6
Jilin		0	Specialists and technicians for high-tech industries	5
Heilongjiang		0		0
Shanghai	College degree or above	2		6
Jiangsu		0		0
Zhejiang		0	College degree or above/ Technicians/ Managerial experience	6
Anhui		0		0
Fujian	Master degree or above/ Managerial experience	2		6
Jiangxi	College degree or above/ Intermediate technician Certificate	1		6
Shandong		0	Intermediate professional certificate/ Managerial experience	6
Henan		0		0
Hubei		0		0
Hunan		0	college degree or above/ Specialists and technicians	6
Guangdong	College degree or above/ Managerial experience	1		6
Guangxi		0		0
Hainan		0		0
Chongqing		0		0
Sichuan		0	College degree or above	5
Guizhou		0		0
Yunnan		0		0
Tibet		0		0
Shaanxi		0	College degree or above	4
Gansu		0		0
Qinghai		0		0
Ningxia		0		0
Xinjiang		0		0

Source: author's calculation of China Labor Statistical Yearbook, China Industry Economy Statistical Yearbook

Table 3 Correlations between Variables

	Location Quotient	Policy	Vertical Disintegration	Scale Economy	Proximity
Location Quotient	1				
Policy	0.0662*	1			
Vertical Disintegration	-0.0046	0.0246	1		
Scale Economy	0.0939*	0.0925*	-0.0464*	1	
Proximity	0.2950*	0.1350*	0.0430*	0.0701*	1

* $p < 0.01$, ** $p < 0.05$, *** $p < 0.10$

Source: author's calculation of China Labor Statistical Yearbook, China Industry Economy Statistical Yearbook

Table 4 Industrial Characteristics in Annual Survey Samples (2010)

Variable	Food Processing	Manufacture of Measuring Instrument (High-Tech)	All Manufacturing
Location Quotient	0.92	0.77	0.89
	(0.75)	(1.09)	(0.93)
Vertical Disintegration	0.86	0.96	0.80
	(0.08)	(0.08)	(0.21)
Scale Economy	1.22	0.91	4.59
	(0.41)	(0.46)	(3.29)
Proximity	20.18	4.12	20.68
	(0.81)	(1.89)	(2.60)
R&D Intensity	0.01	0.05	0.03
	(0.00)	(0.00)	(0.59)
R&D Intensity relative to average	0.95	4.03	2.88
	(0.00)	(0.00)	(0.59)
Number of Employment	39,961	22,923	49,183
	(1.22)	(1.53)	(1.70)
Number of R&D employment	13,362	32,578	57,824
	(0.00)	(0.00)	(1.16)
Output (Billion)	112.67	21.33	87.74
	(1.27)	(1.87)	(1.82)
Number of Firms	826	194	552
	(1.09)	(1.50)	(1.91)
Industry Sales (Billion)	111.83	17.37	87.20
	(1.26)	(1.93)	(1.83)
Total Profits (Billion)	7.56	1.79	6.15
	(1.26)	(1.66)	(1.74)

Source: author's calculation of China Labor Statistical Yearbook, China Industry Economy Statistical Yearbook

Note: coefficient variation (standard deviation/mean) in parenthesis

Table 5 Estimation Results

	Food Processing	Manufacture of Measuring Instrument (High-Tech)	All Manufacturing
Policy	0.1348*	0.2225*	0.0312
	(0.001)	(0.000)	(0.402)
Vertical Disintegration	-0.3313***	-0.0016	-0.0047
	(0.070)	(0.990)	(0.903)
Scale Economy	0.0040	0.2879*	0.0084*
	(0.946)	(0.002)	(0.000)
Proximity	-0.0045	-0.0135**	0.0060*
	(0.167)	(0.014)	(0.000)
Constant	0.8871*	1.4096*	0.3877*
	(0.000)	(0.000)	(0.000)
Year Effects	Yes	Yes	Yes
Province Effects	Yes	Yes	Yes
Observations	279	264	5416
Adjusted R2	0.947	0.925	0.159

p-values in parentheses

* $p < 0.01$, ** $p < 0.05$, *** $p < 0.10$

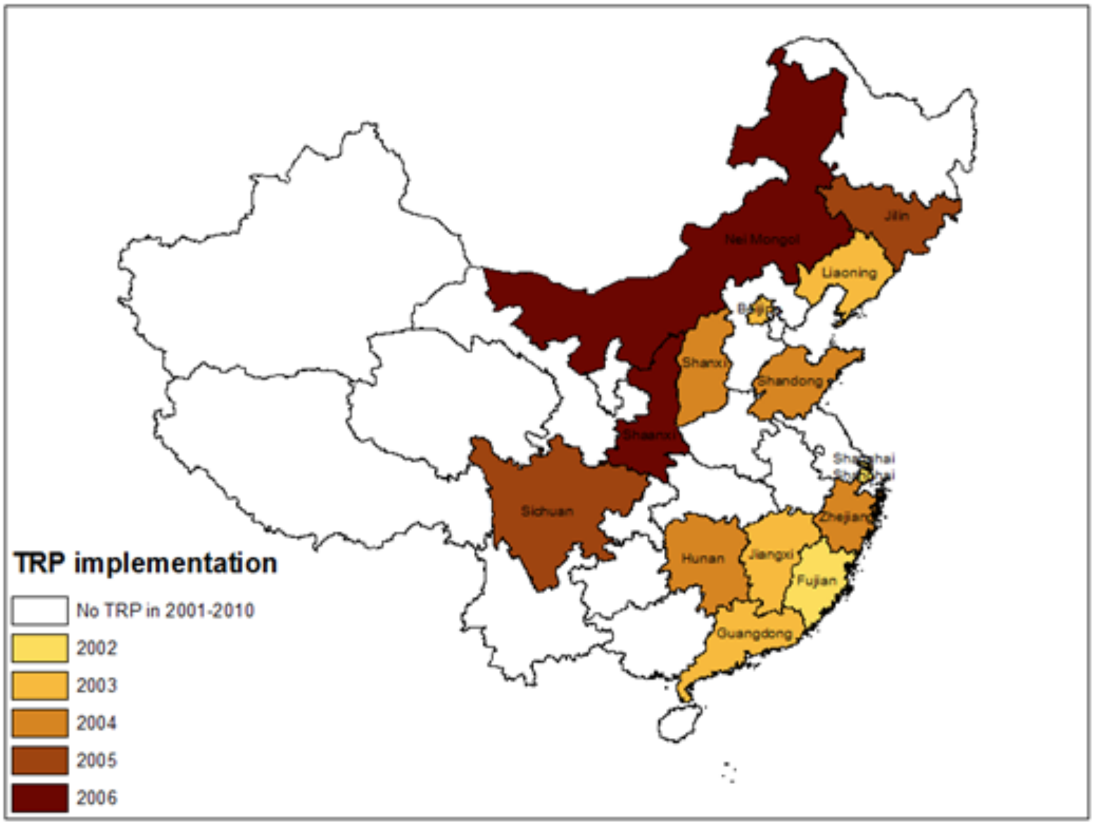
Table 6 Results Validation for Food Processing

	(1)	(2)	(3)	(4)	(5)	(6)
Policy	-0.0773	-0.0680	0.1303*	0.1293*	0.1293*	0.1348*
	(0.355)	(0.472)	(0.001)	(0.001)	(0.001)	(0.001)
Vertical Disintegration				-0.2621***	-0.2621***	-0.3313***
				(0.090)	(0.091)	(0.070)
Scale Economy					-0.0001	0.0040
					(0.999)	(0.946)
Proximity						-0.0045
						(0.167)
Constant	0.9489*	0.9685*	0.4907*	0.7245*	0.7245*	0.8871*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year Effects	No	Yes	Yes	Yes	Yes	Yes
Province Effects	No	No	Yes	Yes	Yes	Yes
Observations	310	310	310	310	310	279
Adjusted R^2	-0.001	-0.030	0.949	0.949	0.949	0.947

p-values in parentheses

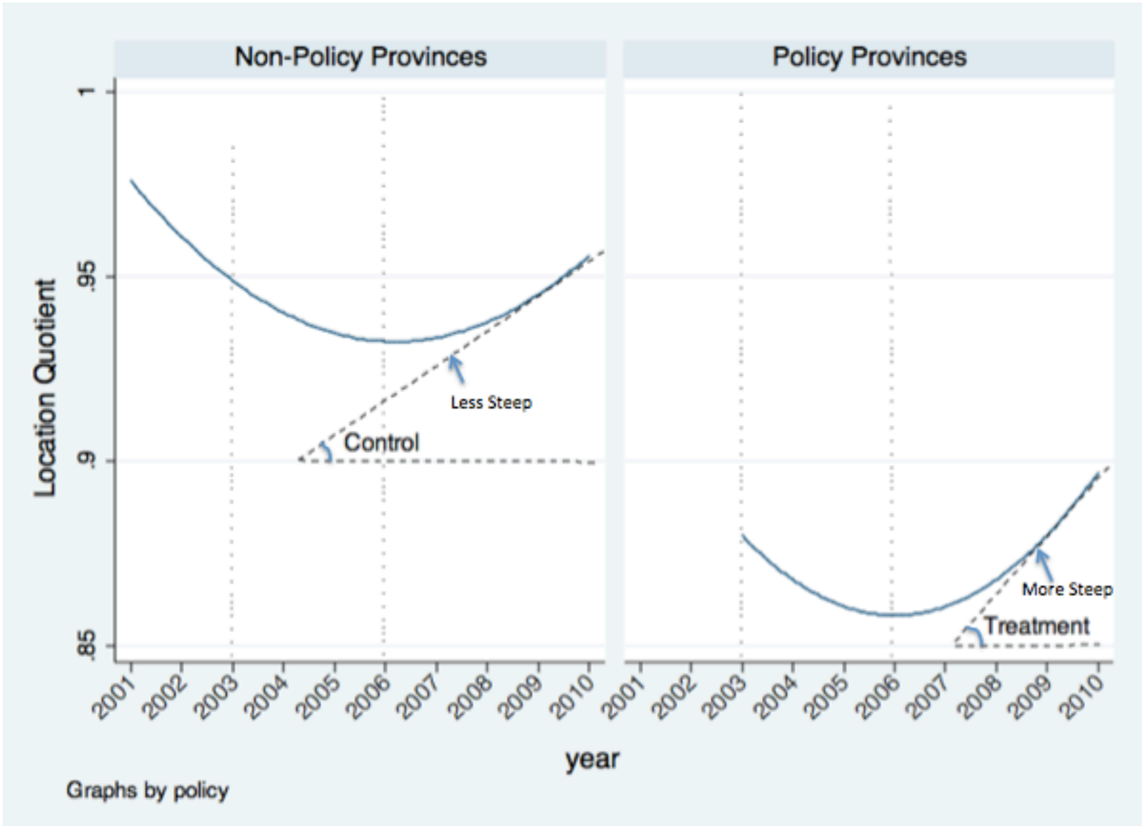
* $p < 0.01$, ** $p < 0.05$, *** $p < 0.10$

Figure 1 Geographic Pattern for TRP Implementation



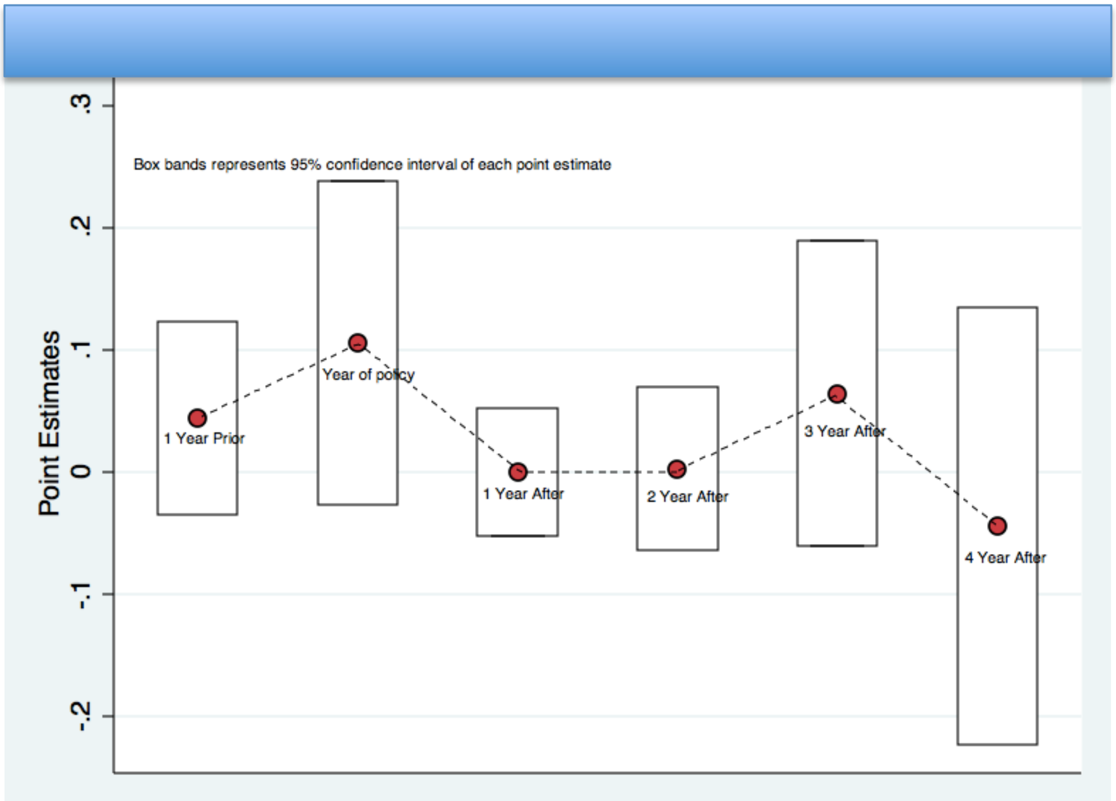
Source: http://www.china.com.cn; http://chinaneast.xinhuanet.com; http://news.eastday.com; http://politics.people.com.cn; (Zhang, 2009)

Figure 2. Location Quotient in Food Processing Industry (2001-2010)



Source: author's calculation of China Labor Statistical Yearbook, China Industry Economy Statistical Yearbook

Figure 3. Causality Test for TRP Policy and Agglomeration Relationship



Source: Author's calculation following Autor (2003), Angrist and Pischke (2008).

Appendix 1. Overview of Missing Data

Variable	Food Processing	Manufacture of Measuring Instrument (High-Tech)	All Manufacturing
Vertical Integration	0	14	159
	0.00%	4.52%	2.56%
Scale Economy	0	13	141
	0.00%	4.19%	2.27%
Proximity	31	31	620
	10.00%	10.00%	10.00%
Total Imputed Data	31	58	920
Observations	310	310	6,200
% Imputed Data	10.0%	18.7%	14.8%