The Dynamics of Economic Policy and Regional Specialization: Evidence from China's High-tech Industry

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Abstract: This paper investigates the effects of economic policy on regional specialization of China's high-tech industries for the period 1996 to 2005. Results indicate that the average level of regional specialization increases over years. Moreover, high-tech industry sector is highly localized in coastal regions. Using a dynamic panel data approach, we find that the implementation of high technology oriented export policy and subsidies for science and high technology activities encourage regional specialization, whereas local government's protections for local high-tech enterprises impede it. The empirical study also confirms the important role of high-skilled labor in determining regional specialization.

Keywords: economic policy; specialization; high-tech industry; dynamics

1 Introduction

Since reform and opening up in 1978, China's fast-growing development has drawn worldwide attention. Despite its rapid economic growth, china still confronts huge challenge to transform its economic pattern to a new one featured with more technology innovation and less consumption. Against this background, policymakers of central government gradually realize the importance of science and high-tech technology in the Age of Knowledge Economy, and they began to make specific plans for the development of high-tech industries in China. During the past few decades, the State Council of China has issued series long-term plans, such as Torch Program (1988) and the Strategy of Rejuvenating Trade through Science and Technology (1999), as national guidelines for accelerating development of high-tech industry. With the implementation of various high-tech programs, China's industrial structure has undergone dramatic changes: high-tech industries are rapidly growing and continue to play an increasingly important role in stimulating export and upgrading traditional manufacturing industries.

Economic reforms have accelerated growth and increased political and economic decentralization, such that local governments have been endowed with greater authorities and more responsibilities. They are authorized not only to enforce state high-tech programs under their jurisdiction but also to issue programs and policies for promoting local high-tech industries. Since 1990s, Local governments have been focusing more on high-tech industries and their locations, as high-tech industrial specialization is considered to be highly related with local economic growth. Regional preferential policies, such as taxation reduction or exemption are instruments commonly used to attract foreign direct investment (FDIs) and Multinational Corporation (MNCs). Local governments also compete aggressively for high-tech enterprises and highly skilled labors from home and abroad through the establishments of various industrial parks or bases. Consequently, questions arise whether such economic policies have worked effectively and how regions are specialized in high-tech industry over years.

In addition to the influence of economic policies, other driving forces are also proposed to explain regional specialization. Neo-classical trade theory emphasized the effect of region-specific comparative advantages on specialization. With the emergence of the New Economic Geography in 1990s, most of recent researches have confirmed the close relationship between transport costs and industrial agglomeration (Krugman, 1991). So far, issues on China's regional specialization have been studied by a lot of literatures. Young (2000) investigates the specialization of five sectors in China between 1978 and 1997 and finds convergence in the structure of output. On the contrary, Bai et al. (2004) calculates the Hoover coefficient using more disaggregated data of 32 2-digit industries and finds specialization in China increased over the period 1985 to 1997. Consistent with the conclusion of Bai et al., recent studies have provided more evidence supporting the steadily increasing trends of regional specialization in China since 1980s (Wen, 2004; Catin, 2005; Lu and Zhao, 2009; Ge, 2009). These studies focus on the manufacturing sector as a whole and partially include some high-tech industries, such as telecommunication equipment manufacturing or pharmaceuticals. However, to our knowledge, there have been very little empirical studies of the possible impact and significance of economic policy on regional specialization of high-tech industries in China.

Thus, this paper attempts to fill this gap with a complete investigation of the trends and extent of regional specialization of high-tech industries during the period of 1996 to 2005. We find that the average level of regional specialization show increasing trends over years and most high-tech industries are highly localized in coastal regions. Furthermore, using the dynamic panel approach, the empirical study provides evidence supporting the close relationship between economic policy and regional specialization. Specifically, the implementations of high-tech oriented export policy and subsidies for science and high technology activities have positive effects, whereas local government's protection for local high-tech industries decreases the level of regional specialization. The empirical study also confirms that a high-skilled labor is an important determinant of regional specialization.

The reminder of this paper is organized as follows: in section 2, we present the measures and data applied in this paper. In section 3, we investigate how region are specialized in high-tech industries, focusing on trends and changes of regional industrial structure. In section 4, using a dynamic panel approach, we empirically examine the impact of economic polices on regional specialization as well as control for other driving forces proposed by theories. The conclusion and some policy suggestions are proposed in section 5.

2. Measures and data

A number of measures have been constructed to measure the geographic distribution of production activities. It is worth noting that calculation results of each measure may varies significantly because of different database and classification of industries. To keep consistency and comparability of measures, in this paper, we primarily use the variants of dissimilarity measures based on the Krugman K-spec index (1991) to investigate specialization.

For a country with J geographic units and I industries, the output of industry i in region j is denoted as q_{ij} (i=1, 2, … , 5. j= 1, 2, … , 30) the dissimilarity index of specialization $DIS_{j,k}$ are defined as:

$$DIS_{j,k} = \frac{1}{I}\sum_{i=1}^{I}\left|S_{ij}^{S} - S_{ik}^{S}\right| \qquad (1)$$

where S^S_{ij} and S^S_{ik} represent the levels of specialization of region j and region k in industry i:

$$S_{ij}^{S} = \frac{q_{ij}}{\sum_{i=1}^{I} q_{ij}} \text{ , and } S_{ik}^{S} = \frac{q_{ik}}{\sum_{i=1}^{I} q_{ik}} \qquad (2)\text{-}(3)$$

The dissimilarity index $DIS_{j,k}$ measures the dissimilarities between industrial structure for region j and region k. The value of $DIS_{j,k}$ equals zero if region j has an industrial structure identical to region k and takes a maximum value of $2/I$ if region j has no industries identical to region k.

The calculation of dissimilarity indices requires data on output across a set of regions and industries. For this paper, we choose 5 high-tech industries defined by the Catalog for High-technology Industrial Statistics Classification (2002) as follows: (1) Aircraft and spacecraft manufacturing (A&S), (2) Electronic and telecommunication equipment manufacturing (E&T), (3) Computers and office equipment manufacturing (C&O), (4) Pharmaceutical manufacturing (P&M), (5) Medical equipment and meters manufacturing (M&M). According to current administrative division of China, we choose 30 provinces as our geographical units and divided them into three coastal regions and four inland regions: Northern coast, Middle coast, Southern coast; Northern inland, Middle inland, Southern inland and Far west inland. The data of high-tech industries are from the National Bureau of Statistics (NBS), China Statistics Yearbook on High Technology Industry (2002, 2003 and 2008), which provides the data on 5 high-tech industries for 30 provinces over the period of 1996 to 2005.

3 Measuring regional specialization of high-tech industries

In this section, we start to investigate the high-tech industrial structure of each region and primarily focus on three questions: how specialized are regions in different periods; the similarity of high-tech industrial structure between regions and which high-tech industry is region specialized.

Table 1a and 1b reports the dissimilarity indices $DIS_{j,k}$ for seven regions, respectively. The national average $DIS_{j,k}$ goes up significantly from 0.101 in 1996 to 0.132 in 2005, indicating that regions become more specialized compared with other regions during the same period. Based on the regional average dissimilarity index $DIS_{j,k}$, southern coast is the most specialized region, whereas southern inland is the least specialized region over years.

Table 1a Regional dissimilarity index of specialization $DIS_{j,k}$ (1995)

	Northern coast	Middle coast	Southern coast	Northern inland	Middle inland	Southern inland	Far west inland	**Regional average**
Northern coast	0.000	0.024	0.088	0.110	0.143	0.056	0.138	0.093
Middle coast		0.000	0.087	0.131	0.149	0.072	0.147	0.098
Southern coast			0.000	0.190	0.230	0.143	0.225	0.146
Northern inland				0.000	0.072	0.069	0.096	0.093
Middle inland					0.000	0.087	0.037	0.096
Southern inland						0.000	0.106	0.080
Far west inland							0.000	0.102
National average								**0.101**

Table 1b Regional dissimilarity index of specialization $DIS_{j,k}$ (2005)

	Northern coast	Middle coast	Southern coast	Northern inland	Middle inland	Southern inland	Far west inland	**Regional average**
Northern coast	0.000	0.107	0.110	0.213	0.139	0.142	0.215	0.132
Middle coast		0.000	0.036	0.253	0.180	0.183	0.257	0.145
Southern coast			0.000	0.286	0.216	0.218	0.292	0.165
Northern inland				0.000	0.090	0.078	0.106	0.147
Middle inland					0.000	0.047	0.090	0.109
Southern inland						0.000	0.114	0.112
Far west inland							0.000	0.135
National average								**0.132**

Focusing on each region, three costal regions have more similar industrial structure, moreover, the dissimilarity index $DIS_{j,k}$ of Middle coast and Southern coast goes down from 0.087 to 0.036, indicating convergence of high-tech industrial structure over years. On the other hand, the inland average dissimilarity index $DIS_{j,k}$ increases from 0.067 in 1996 to 0.082 in 2005[1], which is considerably lower than the national average level during the same period, suggesting that inland regions are also more similar to each other. On the contrary, the dissimilarity indices $DIS_{j,k}$ among

1 Inland average dissimilarity index $DIS_{j,k}$ are calculated based on the $DIS_{j,k}$ reported in Table 1a and Table 1b.

three costal regions and four inland regions increases significantly over years. Therefore, the increase in the dissimilarity index $DIS_{j,k}$ is mainly caused by the widening difference between coastal and inland regional industrial structure. The calculation results of regional dissimilarity index $DIS_{j,k}$ further confirmes that as national average level of specialization increases, the disparities between developed and underdeveloped regions also increases over years.

Table 2a and 2b report the share of high-tech industry output for seven regions in 1996 and 2005. Coastal region accounts for 75.5% of high-tech industry output in 1996, this share continues to increase and reaches 89.6% in 2005, which suggests that coastal region has become the production center for high-tech industry sector in China. Notably, coastal region have further reinforced their positions in M&M, C&O and E&T in 2005.

Table 2a Regional concentration of high-tech industries (1996)

	Coast (%)	Northern Coast (%)	Middle Coast (%)	Southern Coast (%)	**Inland (%)**	Northern Inland (%)	Middle Inland (%)	Southern Inland (%)	Far west Inland (%)
A&S	28.1	11.4	14.9	1.8	71.9	30.8	21.2	19.2	0.7
P&M	62.3	25.0	22.1	15.2	37.9	11.1	16.0	9.7	1.1
M&M	72.0	22.7	41.6	7.7	28.0	6.1	11.9	9.3	0.7
C&O	93.4	19.2	22.6	51.6	6.6	3.7	0.9	2.0	0.0
E&E	83.6	23.3	26.1	34.2	16.5	4.8	4.1	7.3	0.3
Total	**75.5**	**22.5**	**25.3**	**27.7**	**24.5**	**7.7**	**8.2**	**8.1**	**0.5**

Table 2b Regional concentration of high-tech industries (2005)

	Coast (%)	Northern Coast (%)	Middle Coast (%)	Southern Coast (%)	**Inland (%)**	Northern Inland (%)	Middle Inland (%)	Southern Inland (%)	Far west Inland (%)
A&S	28.4	19.5	3.5	5.4	71.5	40.4	13.2	17.5	0.4
P&M	63.9	27.1	26.0	10.7	36.1	11.6	14.2	9.1	1.2
M&M	83.5	23.7	40.3	19.5	16.6	3.5	8.1	4.4	0.6
C&O	98.6	8.0	43.8	46.7	1.4	0.2	1.0	0.2	0.0
E&E	93.9	24.1	31.4	38.4	6.1	1.3	2.6	2.1	0.1
Total	**89.6**	**19.3**	**34.4**	**35.9**	**10.4**	**3.3**	**4.1**	**2.9**	**0.1**

Consequently, as most of high-tech industries agglomerate toward coastal regions, inland regions have experienced sharp drop in the share of high-tech industry output from 1996 to 2005. Nevertheless, A&S is the only high-tech industry that is more localized in inland regions. It has maintained the initial distribution across coastal and inland regions, and the regional share of each region has not changed significantly. Furthermore, Northern inland remains its dominant position with a 40.4% share of A&S output in 2005.

In summary, in this section we calculate the dissimilarity indices and find an increasing divergence of regional industrial structure. These results are consistent with previous studies of Wen (2004) and Lu and Tao (2009), which have found the increasing trends of agglomeration of manufacturing in

China over the past decades. The geographic distribution of high-tech industries can be affected by various agglomerative or dispersed factors. For example, theoretically, Inland regions should be more specialized in A&S since their regional shares are greater than that of coastal regions. However, according to the calculation results, none of these inland regions specialized in A&S. Furthermore, as regions become more specialized, most high-tech industries become more localized in coastal regions. Such contrast can be explained by the implementation of various industrial policies across regions. Local governments tend to design specific plan for promoting the development of local high-tech industries, such policy intervention may have significant impact on regional industrial structure. In next section, we shall turn to investigate the impact of various economic policies on regional specialization of high-tech industries in China.

4 Econometric analysis

4.1 Econometric specification and method

Our empirical study uses a panel data set of 5 high-tech industries and 30 provinces during the period 1996 to 2005. The utilization of panel data set allows us to control for time-invariant individual heterogeneity and the lagged effect of variables.

We start by estimating a simple static panel model in the following specification:

$$SPEC_{jt} = \alpha + \beta X_{jt} + f_j + \varepsilon_{jt} \tag{4}$$

where $SPEC_{jt}$ is the dissimilarity index of specialization DIS_j calculated in section 2, which measures the extent of regional specialization for region j in year t. X_{jt} is the vector of independent variables. α and β denote the constant and coefficient vectors respectively. f_j stands for the time-invariant fixed effect. (e.g., local reserves of mineral resources or regional cultural backgrounds). The error term ε_{jt} is assumed uncorrelated with the vector $X1_{jt}$. Consequently; all independent variables are strictly exogenous.

The static specification of Equation (4) indicates that high-tech industrial structure adjusts instantaneously after the implementation of certain economic policy. However, in reality, adjustment often progresses slowly and highly depends on its previous pattern (Bai et.al, 2004). Therefore, a dynamic panel data model is constructed to explore the potential lagged effects of both dependent and independent variables as follows:

$$SPEC_{jt} = \alpha + \delta SPEC_{j,t-1} + \gamma_0 X1_{jt} + \gamma_1 X1_{j,t-1} + \theta X2_{jt} + f_j + \varepsilon_{jt} \tag{5}$$

where $SPEC_{j,t-1}$ is the lagged dependent variable, which measures the lagged impact of regional specialization in previous year t-1. Other independent variables are divided into two groups. In the first group, $X1_{jt}$ and $X1_{j,t-1}$ are the vectors of current and lagged economic policy variables, respectively. In the second group, $X2_{jt}$ is the vector of other controlled variables. δ, γ_0, γ_1 and θ are coefficient vectors. In addition to the assumption in the static model of error term ε_{jt}, we furthermore assume that the error term ε_{jt} is not autocorrelated.

As $SPEC_{j,t-1}$ is positively correlated with the error term due to the presence of individual effects, the inclusion of lagged dependent variable $SPEC_{j,t-1}$ as regressor would induce the biased estimation results of Ordinary Least Squares (OLS) or other common regression methods for panel data set (Bond, 2002). The Generalized Method of Moments (GMM) developed by Arellano and Bond (1991) is commonly adopted to solve this problem. First, the individual effect f_j is eliminated by the first-differencing transformation of Equation (5). Second, under the previous assumption that ε_{jt} is serially uncorrelated, the lagged $SPEC_{j,t-l}$ (l=2,3,…) could be used as valid instruments for the difference term $\Delta SPEC_{j,t-1}$.

Although the first-difference GMM estimator is consistent according to our initial assumption, it may perform poorly as we attempt to explore the times series properties of individual series. The instruments available for the equation in first-differences tend to be weak when the individual series are highly persistent (Bond, 2002). In such case, the system GMM estimator developed by Arellano and Bover (1995) and Bllunell and Bond (1998) provide better estimation results with smaller bias and greater precision. Specifically, the lagged first difference $\Delta SPEC_{j,t-1}$ is also valid as instrument for $SPEC_{j,t-1}$ in the level Equation (5). Moreover, other independent variables $X1_{jt}$ and $X2_{jt}$ which are assumed to be exogenous, serve as their own instruments, indicating the complete time series ($X1_{j,1}$, $X1_{j,2}$,…$X1_{j,t}$) and ($X2_{j,1}$, $X2_{j,2}$,…$X2_{j,t}$) are valid instrumental variables.

4.2 Specification of independent variables

4.2.1 Control for economic policy

(1) High-tech oriented export policy

China has implemented a series of heavy-industry based industrial development strategy in 1950s. Most manufacturing enterprises are designed to locate in inland regions due to national security consideration. The reform and opening-up in 1978 provides a golden opportunity for the development of high-tech industry. Since then, the central government begins to change industry policies from emphasizing heavy-industry to adjusting imbalanced industrial structure and upgrading traditional manufacturing by making full use of high technology. The implementation of "Strategy of Rejuvenating Trade through Science and Technology" in 1999 further confirms the importance of high-tech industry in stimulating the export and transforming trade patterns from labor-intensive to high-technology intensive.

As discussed in section 2, eastern coastal provinces where reform and opening-up were initially performed, have gradually become the center of high-tech industrial production and export since 1980s. After further acceleration of economic opening to inland in 1990s, middle and western regions also implement high-tech export-oriented policy based on the successful experiences of eastern region. Consequently, those export-oriented high-tech industries, such as C&O and E&T manufacturing, grow rapidly and play an important role in transforming regional structure. The importance of high-tech oriented export policy is measured by the variable openness to export, which is defined as the share of regional export in regional high-tech industrial output.

(2) Subsidies for Science and Technology (S&T) activities

Local governments tend to promote high-tech industries and high-tech enterprises through various subsidies. A subsidy for science and technology (S&T) activities is one of the most direct instruments. However, more subsidies form governments do not indicate higher level of regional specialization of high-tech industries. Indeed, the impact of subsidy on regional industrial structure is highly related to the allocation of subsidies across high-tech industries. Specifically, local governments could focus on the balanced development of high-tech industries as a whole, consequently making the allocation of subsidies more evenly spread across high-tech industries. In contrast, if local governments prefer to implement a specialized high-tech industrial policy, the particular high-tech industry targeted would receive more subsidies than others.

We construct variable, subsidies for S&T, which is defined as the index of subsidy allocation ISA_j as a proxy to measure the impact of local governments' subsidies on regional high-tech industrial structure:

$$ISA_j = \sum_{i=1}^{I} \left| \frac{subsidy_{ij}}{subsidy_j} - \frac{1}{I} \right|, \quad j = 1,2,\ldots,5 \tag{6}$$

for region j, $subsidy_{ij}$ is the percentage of high-tech industry i's subsidy in total $subsidy_j$. In an extreme case, if government equally allocates subsidies across industries, each high-tech industry gets $1/I$ of total subsidies. Thus the ISA_j index measures the differences between actual allocation ratio and equal allocation ratio for each high-tech industry. Significant differences indicate high level of concentration of subsidies in few high-tech industries.

(3) State-level high-tech industrial base (SHIB) policy

In 1980s, the emerging high-tech industrial cluster represented by Silicon Valley has received a great deal of attention throughout the world. Over the same time period, the State Council of China officially approved the first SHIB in Jiangsu province. By 2005, 113 high-tech industrial bases have been established across 17 provinces in China. These industrial bases facilitate the high-tech industrial agglomeration in two ways. First, some knowledge, such as tacit knowledge cannot be formalized or written down; therefore, knowledge spillovers are expected to be more localized within the geographic scope of industrial base. Second, although State Council approves the establishment of high-tech industrial base, local governments are responsible for their overall administration and guidance. Consequently, various preferential policies are often implemented to attract high-tech enterprises. Therefore, high-tech enterprises tend to agglomerate in SHIBs to benefit from knowledge spillovers and various local preferential policies.

Regions with better-developed SHIBs would be expected to attract more high-tech enterprises to agglomerate in their SHIBs. We thus construct a time-vary dummy local SHIB to measure the existence of SHIBs in one province. The variable takes a value of 1 if one province has at least one SHIB in any given year.

(4) Local protectionism

Central government's emphasis on high-tech industry stimulates local governments to make strategic decisions about strategic high-tech industries. In addition to the economic policies mentioned above, local governments tend to promote local high-tech industry through various invisible protections. Since 1978, the economic reform has led to rapid economic growth as well as further political and economic decentralization. As local governments are endowed with greater authorities, they more aggressively intervene in local high-tech product market and protect local high-tech enterprises. Local protectionism is in variety of forms. For example, according to current tax law in China, qualified high-tech enterprises could enjoy 15% reduction of income tax rate. However, the identification of high-tech enterprise is under the administration of local government, therefore, local high-tech enterprises tend to pass the identification more easily with the protection of local governments.

Unlike the trade barriers among countries in the context of international trade, it is very difficult to measure local governments' protection for local high-tech enterprises within a country directly. We thus turn to consider the outcome of protectionism. Specifically, local high-tech enterprises could gain surplus profits due to various forms of local protectionism that significantly improves their products' competitiveness in local markets. We employ a variable local profit ratio, which is defined as the percentage of profit in total sales to measure the impact of local protectionism on regional specialization. Since higher profit ratio indicates higher local protectionism, we would expect the variable has a negative effect on regional specialization.

4.2.2 Controls for others

Although we mainly focus on the impact of economic policy on regional specialization of high-tech industries, it is still necessary to control for other related determinants of regional specialization proposed by theories.

(1) Knowledge resources

Most existing literatures have confirmed the impact of fixed regional resource endowments on regional specialization. For example, due to the high dependence of some raw materials, most extractive industries highly agglomerated in regions with abundant coals or oils. In contrast to those general manufacturing, high-tech industry is characterized as knowledge-intensive, indicating that regions have more knowledge resources would be more specialized in high-tech industries. However, it is difficult to measure the invisible knowledge flows empirically. We turn to focus on the carriers and transmitters of knowledge. The most effective way to transfer knowledge is by face-to-face communication of high-skilled labors. Therefore, we construct a variable high-skilled labor intensity, which is defined as the share of scientists and engineers in regional total employee weighted by national average, as a proxy for the impact of regional comparative advantages of knowledge resources.

(2) Local transportation conditions

Since 1980s, both central and local governments have launched large-scale constructions of local infrastructure. The construction of railways and highways may have significant impact on the geographic distribution of high-tech industries since it greatly reduce the transport costs. High-tech enterprises prefer to locate in regions with better provision of transport network, consequently, they could benefit from lower local transaction costs as well as more convenient and rapid connection with other regions. We employ a variable transportation per capita, which is defined as the logarithm of total length of railways and highways for a region weighted by regional population, to measure the impact of local transportation conditions on regional specialization.

Table 3 Definitions and statistics of variables

	Definition	Mean	SD	Min	Max
Dependent variable					
SPEC	Dissimilarity index of regional specialization DIS_j	0.201	0.057	0.111	0.336
Independent Variable					
Openness to export	Regional export divided by regional total output	0.136	0.170	0.000	0.716
Subsidies for S&T	Index of subsidy allocation ISA_j	1.133	0.304	0.157	1.600
Dummy SHIB	Dummy SHIB =1; if region j has at least one SHIB in year t. Dummy SHIB =0; if region j has no SHIB in year t	0.240	0.428	0.000	1.000
Local profit ratio	The share of enterprise profit in sales in one region divided by national average level	0.049	0.056	-0.420	0.193
High-skilled labor intensity	The share of scientists and engineers in regional total employee divided by national average level	0.697	0.301	0.133	1.592

Transportation per capita	The logarithm of total length of railways and high-ways of one region divided by regional population	1.160	0.211	0.626	1.759

Table 3 summarizes definitions and statistics of variables. The data of SHIBs are from Torch High Technology Industry Development Center, Ministry of Science and Technology of China. The data of regional population and length of railways and highways are from (NBS) China Statistical Yearbook (1997-2006); data of other variables are from (NBS) China Statistics Yearbook on High Technology Industry (1997-2006).

4.3 Estimation results

Table 4 reports the estimation results of the static model of regional specialization with three estimation methods: pooled OLS, fixed effects, and random effects. Focusing on economic policy variables, the estimation results vary significantly across estimation methods. We thus perform two tests to determine the proper specification for the static model. The F test accepts the significance of individual-specific effects at 1% level, confirming the validity of the specification of fixed effects model. Moreover, the corresponding p-value of Hausman-statistic is smaller than 1%, rejecting the null hypothesis that the individual-specific effects are uncorrelated with the independent variables. Taken together, the specification of the fixed effects model is more preferred than the pooled OLS and random-effects model.

Table 4 Estimation results of static model of regional specialization

	Pooled OLS	Fixed effects	Random effects	Fixed effect with AR(1) disturbance
Economic policy				
Openness to export	-0.090*** (0.013)	0.034***(0.011)	0.015 (0.011)	0.007**(0.003)
Subsidies for S&T	0.002 (0.009)	0.0002 (0.007)	0.004 (0.006)	-0.001 (0.002)
Dummy SHIB	0.007 (0.005)	0.010**(0.004)	0.008**(0.004)	0.001*(0.001)
Local profit ratio	0.038 (0.040)	-0.003 (0.025)	-0.012 (0.024)	-0.018*(0.010)
Control for others				
High-skilled labor intensity	0.078***(0.009)	0.048***(0.008)	0.054***(0.007)	0.006***(0.002)
Transportation per capita	0.083***(0.014)	0.052**(0.020)	0.082***(0.017)	0.001 (0.009)
Constant	0.056***(0.014)	0.010***(0.024)	0.061***(0.019)	0.216***(0.013)
AR(1)	-	-	-	0.794***(0.033)
R-squared	0.559	0.886	0.303	0.993
Adjust R-squared	0.550	0.871	0.289	0.992
F test (p-value)	-	26.178(0.000)	-	4.528(0.000)
Hausman test (p-value)	-	-	31.882(0.000)	-
Observations	300	300	300	270

Note: (1) The numbers in brackets are standard errors;

(2) ***, **, * denotes significance higher than 0.01, 0.05, and 0.10, respectively.

Focusing on the estimation results of fixed-effects model, local openness to export and the SHIB dummy variable have positive and significant coefficients at 1% and 5% level, respectively, which suggests high-tech oriented export policy and the establishment of SHIB have positive impact on regional specialization. While the coefficient of subsidies for S&T activities is positive but insignificant, providing only weak evidence supporting the positive effect of this policy. Furthermore, the coefficient of local profit ratio is negative but insignificant. Therefore, we cannot argue confidently that local governments' protection for local high-tech enterprises has a negative effect on regional specialization. As for other control independent variables, the estimation results confirm that local high skilled labors, transportation condition have positive and significant effects on regional specialization.

To test the robustness of the specification of the fixed effects model, we loosen the initial assumption of the error term ε_{jt} and allow it follow the first-order autocorrelation as follows:

$$\varepsilon_{jt} = \varphi\varepsilon_{j,t-1} + \mu_{jt} \tag{7}$$

The last column of Table 4 reports the estimation results of the fixed effects model with AR (1) disturbance. It is worth noting that the estimation result varies significantly as we control for the potential first-order autocorrelation of error terms. Compared with the fixed effects model, the coefficients of all economic policy variables become smaller. Moreover, the coefficient of local profit ratio variable becomes significant whereas subsidies for S&T variable is still statistically insignificant. More importantly, the inclusion of the first-order autocorrelated error term in the static model allows us to partially account for the lagged responses of regional specialization. The positive and significant coefficient (0.794) of AR(1) confirms the existence of first-order autocorrelation of the error term, which suggests that the specification of the static model is incorrectly specified. Therefore, we turn to investigate the dynamic specifications that yield more consistent estimation results.

We estimate the dynamic model of regional specialization with first-difference and system GMM methods. Taking into account that two many instrumental variables would weaken the Sargan test by overfitting the endogenous variable, we include one lag of both dependent and independent variables for economic policy in the specification of dynamic model. Table 5 reports the estimation results of first-difference GMM and system GMM methods in the first and second columns, respectively. For both estimations, the Sargan test does not reject the null hypothesis that the overidentifying restrictions are valid, and the Arellano-Bond autocorrelation test indicates that there is no evidence of second-order serial correlation.

To assess the bias and precision of first-difference GMM and system GMM estimators, we first investigate the stationary properties of each time series by estimating a simple AR (1) model for all independent variables. (Estimation results and specification in details are presented in Appendix B.) According to the estimation results of the AR (1) model, all variables are found to be highly persistent. Second, we estimate the dynamic model with pooled OLS and Least Squares Dummy Variables (LSDV) method and report the estimation results of each method in column three and four in Table 5, respectively. As Roodman (2009) suggested, given that the lagged explainable variable $SPEC_{j,t-1}$ is positively correlated with the error term, the coefficient of $SPEC_{j,t-1}$ is biased upwards in the OLS estimation but is biased downwards in the LSDV estimation. Therefore, a proper estimate of the true parameter should lie within the range of 0.704 to 0.929. By comparison, the coefficient of $SPEC_{j,t-1}$ in the first-difference GMM estimations (0.546) is far below the lower limit (0.704). These results are in line with Blundell and Bond (1998), confirming that the instruments available for the equations in the first-differences are likely to be weak when the individual series exhibits strong persistence. By contrast, the coefficient of $SPEC_{j,t-1}$ in the system GMM estimation lies suitably within the bonds defined by OLS and LSDV estimation, and thus we prefer the estimation results obtained from the system GMM methods.

Table 5 Estimation results of dynamic model of regional specialization

	First-difference GMM	System GMM	Pooled OLS	LSDV
Lagged effect SPEC				
SPEC (-1)	0.546***(0.043)	0.894***(0.013)	0.929***(0.025)	0.704***(0.049)
Economic policy				
Openness to export	0.010**(0.004)	0.009***(0.003)	-0.006 (0.012)	0.012 (0.013)
Openness to export (-1)	-0.002 (0.004)	-0.001***(0.004)	-0.005 (0.012)	0.003 (0.012)
Subsidy for S&T	-0.001 (0.002)	0.003*(0.002)	0.001 (0.005)	0.001 (0.005)
Subsidy for S&T (-1)	-0.002 (0.001)	-0.002**(0.001)	-0.001 (0.005)	-0.001 (0.005)
Dummy SHIB	0.011***(0.005)	0.0002 (0.001)	0.002 (0.002)	0.007**(0.003)
Local profit ratio	-0.006**(0.005)	-0.038***(0.008)	-0.038*(0.020)	-0.037*(0.020)
Local profit ratio (-1)	0.002 (0.004)	-0.015**(0.007)	-0.015 (0.018)	-0.018 (0.019)
Control for others				
High-skilled labor intensity	0.014***(0.001)	0.018***(0.002)	0.011***(0.004)	0.023***(0.006)
Transportation per capita	0.028***(0.008)	0.003 (0.002)	0.002 (0.006)	-0.016 (0.016)
Constant	0.049***(0.008)	0.011***(0.003)	0.012**(0.006)	0.065***(0.019)
Sargan test (p-value)	24.034 (0.241)	23.037 (0.400)	-	-
AR (2)	0.803	0.846	-	-
Observations	240	270	270	270

Note: (1) The numbers in brackets are standard errors;
(2) ***, **, * denotes significance higher than 0.01, 0.05, and 0.10, respectively.

According to the estimation results of the system GMM method, the coefficient of lagged $SPEC_{j,t-1}$ is positive and statistically significant at the 1% level. As we expected, the positive impact of previous regional specialization indicates that the adjustment of regional high-tech industrial structure is a slow process and highly depended on its historical pattern. This result is consistent with the conclusion of Bai et.al. (2004) in the case of regional specialization of manufacturing in China.

As for economic policy variables, openness to export has a positive and significant coefficient, which confirms the impact of economic opening and high-tech export-oriented policy on regional specialization. Our results are also consistent with the findings in Ge (2008), further confirming that export-oriented high-tech industries have higher degree of agglomeration in China. Regions with more openness to foreign market would attract more FDIs and MNCs to invest in those export-oriented high-tech industries, and thus tend to have higher level of specialization of high-tech industries.

The contemporaneous coefficient of local governments' subsidies for S&T activities is positive and significant, indicating that local governments prefer to promote local specialization through allocating subsidies disproportionately across high-tech industries. Consequently, the share of the high-tech industry promoted in total industrial output increases rapidly, thereby increasing of the degree of regional specialization.

The estimation result reveals that the establishment of SHIBs has positive but insignificant coefficient, which gives us confidence to question whether these SHIBs could successfully attract high-tech enterprises or not. Our finding is in line with the study of Zhao et.al. (2008), who argues that although local governments consider SHIBs as one of the most important instrument to promote local high-tech industries, the actual development of SHIBs is still in its infancy stage, with the scale of most SHIBs being quite small. Moreover, the efficiency of SHIBs could also be weakened by other developed zones which were established prior to SHIBs yet provide roughly similar preferential policies, or by those high-tech enterprises located outside SHIBs but still be eligible to enjoy the preferential policies for SHIBs.

Local profit ratio variable has a negative and highly significant coefficient, suggesting that local protection for high-tech industries has a negative effect on regional specialization. This result provides strong evidence supporting our hypothesis that local high-tech enterprises tend to obtain higher profits under the protection of local governments. As a result, protection deteriorates segmentation of domestic high-tech product market, eventually impeding regional specialization of high-tech industries.

In addition to the contemptuous impact of economic policy, Table 6 summaries the short-run effect, which is measured by the coefficient of γ_0 and the long-run effect, which is measured by $(\gamma_0+\gamma_1)/(1-\delta)$ for each economic policy variable (The dummy SHIB variable is not reported here due to its insignificance). According to these calculation results, the implementation of economic opening and high-tech oriented export policy, subsidies for S&T activities have positive long-term effects. On the contrary, local protectionism has a negative long-term impact of on regional speciation.

Table 6 Short-run and long-run effect of economic policy

	Short-run effect	Long-run effect
Openness to export	0.009	0.075
Subsidies for S&T	0.003	0.009
Local profit ratio	-0.038	-0.500

As for other controlled variables, we find that high-skilled labor intensity variable has positive and significant coefficient at 1% level, which confirms our previous hypothesis that regions with higher high-skilled labor intensity tend to have comparative advantage of knowledge resources. Consequently, such comparative advantage would facilitate the regional specialization of high-tech industry. We do not find a significant impact of local transportation on regional high-tech industrial specialization; the coefficient of transportation per capita is positive but insignificant. Considering the time period of our empirical study, regional disparity in road and railways has been greatly diminished due to the large-scale construction of infrastructure in inland regions over years. Moreover, the less dependency of high-tech industry on natural resources endowments also indicates that the variation of transport costs might have little impact on regional specialization of high-tech industries.

In summary, the specification of system GMM model allows us to explore the dynamic features of regional high-tech industrial structure as well as the impact of economic policies. These estimation results indicate that various economic policies have a mixed effect on regional specialization in high-tech industries. The implementation of high-tech oriented export policy and subsidies for S&T activities have significant and positive effects on regional specialization; whereas local governments' protection for local high-tech enterprises decrease the level of regional specialization. Moreover, we also find the significant impact of knowledge resources measured by high-skilled labor intensity, on regional specialization of high-tech industries in China. Taken together, these estimation results provide an explanation for the increasing concentration of high-tech industrial production activities in eastern coastal regions. Although the national average level of regional specialization increases steadily over years, the existence of local protectionism seriously obstructs the diffusion of high-tech industrial production activities from coastal regions to inland regions. By comparison, most industrial transfer occurs within coastal regions, leading to the convergence of industrial structure between middle and southern coastal regions over years. Consequently, inland regions could barely benefit from the rapid growth of high-tech industrial sector in coastal regions. Regional specialization increases at the expense of growing discrepancies between inland and coastal regions.

4. Conclusion

This paper empirically examines the impact of economic policies on regional specialization of 5 high-tech industries during the period 1996 to 2005 in China. We first calculate the dissimilarity index of specialization to investigate trends and changes of regional specialization of high-tech industries in China. Our findings suggest that with China's further openness and involvement of global economic integration, the average level of regional specialization of high-tech industries increases steadily during the period of 1996 to 2005. More importantly, most high-tech industries are currently highly agglomerated in coastal region. Second, using a dynamic panel data method, this paper further explores the dynamic features of both regional specialization and economic policies simultaneously. The estimation results confirm the impact of economic policy on regional specialization of high-industries in China. We find that high-tech oriented export policy and subsidies for S&T activities have positive effects whereas local governments' protection for local high-tech industries and enterprises obstruct regional specialization. Furthermore, our empirical study also provides evidence supports highly skilled labors that could transmit knowledge flows as an essential determinant of regional specialization.

Similar to international trade between countries, interregional trade within a country could also enhance regional welfare through rational specialization across regions. Therefore, our study provides some policy implications for both central and local governments of China. First of all, central government should further accelerate economic openness in inland regions with various macro-level preferential policies, facilitating the transfer of some export-oriented high-tech industries from eastern coastal region to inland regions. Second, local governments of inland regions should pay more attention to promote local high-tech industries that already have a comparative advantage, such as A&S manufacturing. Third, the significant negative impact of local protectionism suggests that further reducing entrance barriers and encouraging domestic market unification would play a more important role in stimulating regional specialization. However, the lagged effects of previous specialization pattern indicate that inland governments require more effort and time to catch up with their counterparts in eastern coastal regions.

Our study is a preliminary exploration on the significant impact of economic policies on regional industrial structure of high-tech industries. The specification of dynamic panel model confirms our initial assumption that both industrial structure adjustments and the impact of economic policies are dynamic processes. Nevertheless, unlike on the high-tech industries that obtain direct promotion form both central and local governments in recent years, the effects of economic policies on general manufacturing may vary significantly across regions. Therefore, it would be worthwhile to extend our study on the dynamics of regional specialization and localization of manufacturing with more disaggregated industrial data in future research.

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Appendix A

To investigate the stationary properties of each series, we first perform two standard unit root tests and report the results in Table A1. These results indicate that for all lagged variables, the unit root tests reject the null hypothesis that series has a unit root. Table A2 reports the estimation results of the simple AR(1) specifications for each time series. It is found that all series but local profit ratio has a positive and significant coefficient higher than 0.900, which provides strong evidence supporting the high persistence of each series.

Table A1 Unit root tests for time series

	LLC test (p-value)	Fisher-ADF test (p-value)
SPEC	-8.979 (0.000)	79.474 (0.047)
Openness to export	-12.424 (0.000)	85.930 (0.016)
Subsidies for S&T	-9.911 (0.000)	71.734 (0.054)
Local profit ratio	-9.096 (0.000)	83.597 (0.024)
High-skilled labor intensity	-13.068 (0.000)	112.395 (0.000)
Transportation per capita	-6.271 (0.000)	53.597 (0.707)

Note: (1) Probabilities for Fisher-ADF tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.
(2) The data are balanced for each series.

Table A2 AR(1) specifications for each time series

Specifications		Estimation results		
Dependent variable	Independent variable	Coefficients	Adjust R-squared	Observations
SPEC	SPEC (-1)	0.980 (0.016)	0.929	270
Openness to export	Openness to export (-1)	0.945 (0.030)	0.784	270
Subsidies for S&T	Subsidies for S&T (-1)	0.990 (0.010)	0.564	270
Local profit ratio	Local profit ratio (-1)	0.740 (0.042)	0.080	270
High-skilled labor intensity	High-skilled labor intensity (-1)	0.996 (0.015)	0.645	270
Transportation per capita	Transportation per capita (-1)	0.990 (0.012)	0.964	270

Note: (1) The numbers in brackets are standard errors.
(2) All coefficients are significantly at 1% level.