Economic Growth and Complexity across Chinese Regions: the Role of Cost-saving Production Diffusion☆

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Abstract

We analyze how increases of average local wage levels contribute to economic restructuring and manufacturing industry performance across Chinese regions. In an unbalanced panel of prefectural cities and industries, spanning the years 1999-2007, we employ an instrumental variables approach to identify a causal relationship. We find that rising wages are negatively related to industry performance and show that the effect is concentrated in China's economically most advanced regions. Industries that make intensive use of (low-skilled) labor decline, but appear to expand in locations where wages are comparatively low. We argue that this is in line with a mechanism of cost-saving industry diffusion. Comparing the economic performance of locations where such industries expand to those where they do not, we find that both economic complexity and subsequent per capita income growth increased faster in the former group. On average, the estimated relative increase amounts to 0.10-0.15 standard deviations of the local economic complexity index (ECI), which translates into 1.3-1.8 percent faster capita income growth in the years 2007-2014.

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JEL classification: D24, O11, O14, O47, O53, R11

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1. Introduction

In an abundant and growing body of research, economists stress that increasing the range of activities can be a key ingredient for countries' economic growth and development (Imbs and Wacziarg, 2003; Klinger and Lederman, 2006; Koren and Tenreyro, 2007; Cadot et al., 2011; Mau, 2016). When translating such benefits from economic diversification into policy objectives, the role of finding the right activities is often highlighted. This means that countries should opt for the relatively more sophisticated and advanced activities, so to increase their overall level of "economic complexity", which eventually boosts economic growth (Hidalgo and Hausmann, 2009; Hausmann et al., 2014). Meanwhile, it can be observed that the international division

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of labor makes low-income countries attractive for certain activities, based on the principle of comparative advantage. According to such mechanics, industries may diffuse from high- to lower-cost locations (Rauch, 1993; Antras and Helpman, 2004; Hanson et al., 2005). Often, such industries are considered to be less skill intensive or more labor intensive, which raises the question of how this relates to countries' ambitions to enhance economic complexity.

On the one hand, the diffusion of industries from high- to lower-cost locations might foster the latter's comparative advantage in non-sophisticated production activities. In that case, it might become an obstacle for achieving higher economic complexity and benefiting from its growth-enhancing externalities. On the other hand, diffusing industries might be relatively more sophisticated from the low-cost location's viewpoint (Feenstra and Hanson, 1997), and thereby facilitate diversification into the "right" types of activities. It might also be, that the diffusion of industries, according to classic economic efficiency mechanics, is unrelated to the evolution of economic complexity. To the best of our knowledge, this relationship remains elusive in the existing literature.

In this paper, we address this question empirically, using a panel data set of Chinese industry production during the period 1999-2007, and exploiting information on the location of the industry within China. We first investigate the question whether rising average wage levels (i.e., labor costs) in a specific production location affect the performance of industries. We find that this is not generally the case, but that it does so in places where the overall wage level is relatively high. We confirm that industry performance (as measured by output, sales, employment, or firm activity) is most negatively affected in low-skill and labor-intensive industries. After identifying a subset of industries that experience a relative decline due to wage growth in such locations, we analyze whether these industries expand in lower-cost locations within China. This is also not generally the case. Instead, a relative expansion of such industries can be observed in locations that are relatively closely located to China's high-income regions and where the average relative wage rate in these industries is low. Finally, we ask how locations that attract industry activity from the high-income regions perform in terms of economic complexity. The results we find suggest that attractive locations experience a significantly faster increase in the economic complexity index (ECI) during the period of our sample. On average, this difference amounts to about 0.10-0.15 standard deviations, and suggests that also per capita income growth was about 1.3-1.8 percentage points higher during subsequent years.

Our paper makes several contributions to the literature. First, we provide a new perspective on China's rapid economic growth and declining regional disparity (Li and Xu, 2008; Lemoine et al., 2015; Jain-Chandra et al., 2018). We connect our work to a large body of research pioneered by Hidalgo and Hausmann (2009); Hausmann and Hidalgo (2011) and Hausmann et al. (2014), and to a more general literature on economic diversification, where a variety of factors are found to be relevant; including path dependence (Dosi, 1982, 1988; He et al., 2018), historical comparative advantage (Minondo, 2011), innovative capabilities (Lin, 2012; Petralia et al., 2017), agglomeration (Diodato et al., 2018), knowledge diffusion through migration (Bahar and Rapoport, 2016), and other geographical and institutional conditions (Parteka and Tamberi, 2013). We add to this by highlighting a mechanism of cost-saving industry diffusion, which appears to have a positive impact on economic complexity and subsequent income growth.

Our paper also relates to a broader debate about the end of cheap labor in China, as highlighted, for instance, by Ceglowski and Golub (2007) and Li et al. (2012). While these papers point out that labor costs increase, they do not investigate the consequences of this trend. Empirical work by Donaubauer and Dreger (2016) and Xiong and Zhang (2016) have investigated such consequences for FDI flows and exports, respectively, but remain fairly general when it comes to considerations of cross-regional heterogeneity within China. We argue that this distinction is important, and add to this literature by presenting empirical evidence that rising labor costs may indeed be an obstacle for China's manufacturing industries. However, the end of cheap labor seems to be true only for a number of highly-developed regions, while the rest of China still offers competitive locations for certain manufacturing activities, and might even benefit from wage growth in the most advanced regions.

Following up on this, our third main contribution is the observation that cost heterogeneity within a country can effectively promote the diffusion of industries, and thus diversification, especially when labor costs increase in more developed regions. This finding is in line with studies that look at the location of industries according to factor-endowment theory, such as Bernard et al. (2008). While their paper focuses mostly on the cross-sectional patterns of industry location (within the United Kingdom), we highlight in our work a mechanism where specific activities gradually disappear in one region and emerge in another.[1] Conceptually, our paper also relates to the work of Konings and Murphy (2006), who investigate whether multinational enterprises shift certain activities to their lowest-cost locations.

Overall, our findings suggest that industry restructuring induced through shifting comparative advantage does not necessarily undermine trajectories towards increasing economic complexity. In the case of China, the opposite seems to be the case.

In the following section, we present some additional background information about China's recent economic performance, and emphasize its cross-regional heterogeneity. We also describe the data used for our subsequent analysis. We devote Section 3 to the empirical approach and identification strategy, and present our findings for the relationship between wage growth and industry performance. In Section 4 we evaluate patterns of industry diffusion and analyze its repercussions for the evolution of economic complexity and subsequent per capita income growth. Section 5 concludes with a brief summary of our main findings and points out some limitations and potential directions of future research.

[1] Bernard et al. (2008) also find that changes in relative factor costs are related to changes in industry composition. However, rather than looking at the direction of cost changes and types of industries, they document more generally that variation in relative factor costs over time is related to variation in industry composition over time.

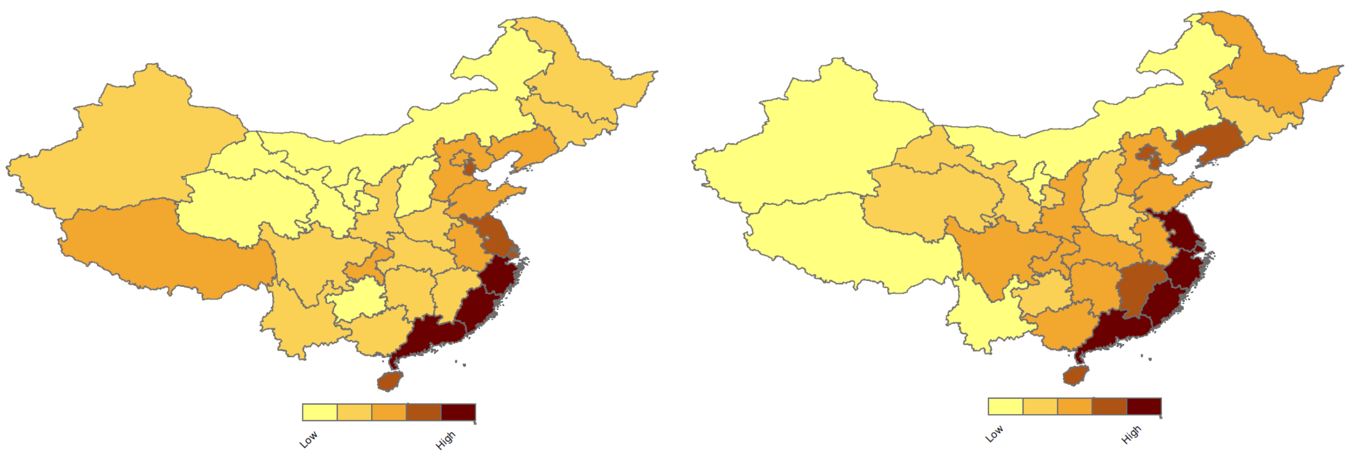
2. Economic performance across Chinese regions

2.1. Background

Following major reforms initiated since the late 1970s, China's recent economic history witnessed an unprecedented increase of living standards and production capabilities. Gradually, the country transitioned towards a market-based economy, where its performance was fuelled by a large labor force, low wages, and extensive participation in international trade. Yet, as China's economy continues to develop, the view that the age of cheap Chinese labor is coming to an end becomes increasingly popular (Li et al., 2012).[2] Taking a closer look at the country, however, reveals that levels of economic development differ greatly across regions. Indeed, substantial intra-national wage differences could be observed already for the 1990s and earlier years (e.g., Gustafsson and Shi, 2002), and also today, most economic activity is concentrated in the provinces located alongside China's eastern and southeastern coastline. More recently, China's inner regions appear to catch-up. This may be partly attributed to efforts of the central government (such as the *One Belt, One Road Initiative*), but also to transfers of capital and technology (Lemoine et al., 2015), or the diffusion of industries into these regions.[3]

Figure 1: Regional Economic Complexity Index (1999 - 2007)

(a) Provincial ECI in 1999 (b) Provincial ECI in 2007



Note: Provincial ECI is calculated using 4-digit industry level employment data, as observed for the indicated years in Annual Survey of Industry Production (ASIP).

In Figure 1, we present two snapshots of cross-regional heterogeneity in terms of an occupation-based ECI.[4] Higher economic complexity is indicated by darker shading and we can observe that the southern and

[2]This view was recently shared also by Tim Cook (CEO of Apple), who asserts that: *"[...] China stopped being the low-cost country many years ago"*. The quote stems from an interview by Adam Lashinsky during the *Fortune Global Forum*, held on December 6th, 2017, in Guangzhou, China.

[3]Note that the period we analyze in this paper ends several years be for the above-mentioned government initiative was launched. Like in our study, Lemoine et al. (2015) do not directly observe capital or other flows across Chinese regions. Their assertion rests on patterns that are in line with rapid and unconditional convergence, as well as convergence in terms of labor productivity.

[4]In this paper, all our computations of ECIs is performed with the user-written command "ecomplexity", available for use in

eastern coastal provinces resemble the advanced regions. Comparing the years 1999 and 2007, we can also observe that the ECI increased in many of the centrally located inner regions of China. This suggests that the evolution of their industry structure has improved their economic complexity and that these regions tend to converge to the highly developed regions at the coast. Panel (b) of Figure 1 further suggests that economic complexity tends to be higher, the closer a province is located to the most advanced regions. This contrasts with the observation for the year 1999 and might be attributed to China's ongoing transition towards a market-based economy and the gradual decline of the state-owned sector.[5] Both the existence of cross-regional heterogeneity as well as the evident dynamics make China an ideal laboratory for exploring the mechanism of cost-saving industry diffusion.

2.2. Data

For our analysis, we exploit detailed information from a Chinese firm-level data set, which is known as the Annual Survey of Industry Production (ASIP). This data has been widely used by researchers to study China's economy. A comprehensive description of the data set is provided by Brandt et al. (2014).[6] Since we are interested in the dynamics and patterns of regional industry performance, we focus on a more aggregate level, namely, the local economy of prefecture-level cities, which represents the second layer of the administrative division in China.[7]

Since any city-level variable we investigate reflects aggregates of several firms, we pay attention to identifying their location carefully. In most cases, this information can be inferred via the first four digits of the so-called "dq-code" in the data, which identifies a city. In some cases (about 4 percent of the firms), this information is inconsistent over time. We impute consistent location codes based on the firm's reported zip code and other information in the original data set. Eventually, we obtain unique city level dq4-codes for all except 35 firms in our sample.

We also undertake basic cleaning of our data. Following Jefferson et al. (2008), we remove firms if they report, in any year, zero, negative, or missing figures for employment, total wage payments, output production, input use, net value of fixed assets, or paid-in capital.[8] Moreover, firms' value-added to sales ratio must range between 0 and 1, and firms' value-added per worker and capital must range within four standard deviations from the annual mean. After these steps, we observe 300,100 individual firms during the period 1998-2007.

Stata at `https://github.com/cid-harvard/ecomplexity`. An output-based ECI reveals similar patterns to the ones presented here.

[5]We provide some further intuition about this mechanism in the following sections.

[6]We note that by using this data, we limit our analysis to the manufacturing sector, which is in line with most other contributions to the literature on diversification and economic complexity. Moreover, the firms reported in this dataset represent mostly large enterprises with annual sales of at least 5 million yuan, which corresponds to about 600,000 US dollars. Besides this, all state-owned firms are included, regardless of their size. Overall, the country-wide aggregates of key variables, such as the number of firms, sales, output, and employment, are very close to the numbers reported in the official statistics, published in the *China Statistical Yearbooks* (see Brandt et al., 2014, for details).

[7]The first layer below China's central government represents Chinese provinces, of which there are 31, including four municipalities and five autonomous regions. Special administrative regions (SAR), such as Hong Kong and Macau, as well as Taiwan, are excluded from the survey.

[8]We also remove firms with fewer than 8 employees, as they often report inconsistent information (Mayneris et al., 2018).

As we aggregate our data, we obtain an unbalanced panel with information at the city-industry level. Since a significant number of cities does not report any data in the year 1998, we restrict our sample to the period 1999-2007, and maintain only those cities and industries that report information throughout the sample. We further exclude four autonomous provinces (Inner Mongolia, Tibet, Xinjiang, and Ningxia), as well as Hainan province, which is an island. Cities in these provinces reveal only very little industry activity in terms of their number of industries and firms. In total, we observe 289 prefecture-level cities in mainland China and distinguish 404 industries, which are classified according to the 4-digit CIC nomenclature.

2.3. Sample summary statistics

Table 1: Regional contributions to industry activity, 1999

Region	Firms	Ouput	Sales	Employ-ment	Value added	Exports	Cities
Coast	0.72	0.76	0.76	0.69	0.74	0.90	85
within: var-coeff.	1.31	1.25	1.26	1.09	1.25	1.50	
Central	0.18	0.14	0.14	0.18	0.16	0.04	98
within: var-coeff.	0.86	0.99	0.99	0.77	0.97	1.34	
West	0.06	0.05	0.05	0.07	0.06	0.01	71
within: var-coeff.	1.84	2.02	2.01	1.85	1.96	2.07	
Northeast	0.04	0.04	0.04	0.05	0.05	0.04	35
within: var-coeff.	1.31	1.82	1.87	1.48	1.86	3.50	
Overall	1.00	1.00	1.00	1.00	1.00	1.00	289
within: var-coeff.	2.00	2.07	2.08	1.69	2.00	2.88	

Note: Authors' calculations based on subsample of Chinese firm-level survey (ASIP).

Our sample features differences across Chinese cities and regions, which are in line with the patterns and discussion at the beginning of this section. Table 1 displays regional contributions to total industrial output production, sales, employment, value added, and exports in 1999. Most industry activity is concentrated in coastal provinces.[9] The numbers range between 69 percent for employment and 90 percent for exports. In terms of firm population, sales, output and employment, central Chinese provinces follow with contributions between 14 and 18 percent, whereas the western and northeastern provinces account for about 5 percent. The variation coefficients denote the cross-city dispersion for each variable within these regions. Comparing coastal and central provinces to the western and northeastern regions, we observe greater dispersion across cities in the latter group. This means that some cities in the western and northeastern provinces are economically much larger than others, and that such differences are less pronounced in the coastal and central Chinese provinces.

Our data set also reveals regional differences in terms of wages paid to employees, which we compute by dividing the total wage bill in a city by its number of employees. Combining this with city-level information

[9] We assign the 25 provinces represented in our sample to four the different regions as follows: *Coast*: Beijing, Fujian, Guangdong, Hebei, Jiangsu, Shandong, Shanghai, Tianjin, Zhejiang; *Central*: Anhui, Guangxi, Henan, Hubei, Hunan, Jiangxi, Shanxi; *West*: Chongqing, Gansu, Guizhou, Shaanxi, Sichuan, Yunnan; *Northeast*: Heilongjiang, Jilin, Liaoning. Qinghai province has been excluded due to too few observations.

on local minimum wage rates and average service sector wages, we can rank cities based on their two highest scores in these individual rankings and split them into five equally sized groups. We are going to refer to these groups as "cost-quintiles" or simply "quintiles" in the remainder of this paper.[10]

Table 2: Contributions to industry activity by cost-quintiles, 1999

Cost-quintile	Firms	Ouput	Sales	Employ-ment	Value added	Exports	Wage CIC 3111	Coast
Top (fifth)	0.59	0.65	0.65	0.56	0.62	0.84	1.36	47
Fourth	0.17	0.16	0.16	0.18	0.17	0.09	1.08	22
Third	0.09	0.09	0.09	0.11	0.09	0.04	1.04	9
Second	0.09	0.07	0.07	0.09	0.08	0.02	0.99	6
Bottom (first)	0.06	0.03	0.03	0.05	0.04	0.01	0.90	1

Note: Authors' calculations based on the subsample of Chinese firm-level survey (ASIP). Each quintile is composed of $289/5 \approx 58$ prefecture-level cities, except for the top quintile, which is composed of 57 cities. The wage rate refers to the average city-level wage rate relative to the median city in industry CIC 3111 (*i.e.*, cement manufacturing).

In Table 2, we observe that the two highest cost-quintiles combined account for about 80 percent of industry output in our sample, and for about 73 and 93 percent of employment and exports respectively. The table also shows that city-level wage rates differ across locations within the same industries, such as cement manufacturing (CIC 3111).[11] Relative to the median city's wage in this industry, top-quintile city wages are on average 36 percent higher, while they are about 10 percent lower in the bottom quintile. The last column in the table indicates that 47 of the 57 top-quintile cities reside in a coastal province, and that 69 out of 85 cities we observe in the coastal provinces belong at least to the fourth cost quintile. This suggests that the economically most advanced regions in terms of economic size and complexity also tend to have the highest average wage level. From such locations we might expect that (some) industries diffuse to inner Chinese regions as wages continue to increase.

2.4. Differential developments across Chinese regions

Before turning to our empirical analysis, we briefly describe some patterns that are suggestive of the mechanism we attempt to identify. In Figure A1(a) we plot the evolution of coastal China's contribution to total output, sales, employment, and firm count over time. Figure A1(b) shows the same for top-quintile locations. Although ranging at different levels, trajectories for the two groups are similar. Coastal and top-quintile cities strive during the late 1990s and early 2000s, until their expansion tends to slow down and reverse around the year 2004. This implies that the rest of China begins to catch-up. In Figure A2, we present comparative patterns for average productivity-adjusted wages (i.e., unit-labor costs). Panel (a) compares cities in coastal provinces to those residing in inner China. Panel (b) compares top-quintile cities

[10]The minimum wage data is the same as the one used by Gan et al. (2016) and Mayneris et al. (2018). Information on service sector wages is retrieved from the *Chinese Cities Statistical Yearbooks*. We base our rankings on averages for the years 1999-2001, as some of these additional indicators are reported only for later years.

[11]Figures for this industry are widely reported in our sample, while other industries are reported as active in only a few locations.

to cities in the remaining quintiles. Again, the patterns are similar: productivity-adjusted wages tend to decrease across China during early years of our sample, but begin to diverge during later years. This suggests that inner and lower-wage regions increasingly have a cost advantage.

Combining the patterns of both figures, we find it plausible to expect cost-saving industry diffusion to occur, and that this facilitates the economic catch-up of China's less developed regions. To test this hypothesis, we first address the question whether rising wages have any effect on industry performance in China. Only then we can turn to an analysis of cost-saving industry diffusion and its repercussions for subsequent economic performance.

3. The effect of local average wage levels on industry performance

In this section, we address our first question: are growing wages an obstacle for industry development in China? To answer this question, we need to identify drivers of wage growth, which make industry development more difficult. Noting that higher wages can also result from demand shocks and industry expansion, we face the challenge of identifying increases in wage rates that are due to factors which are exogenous to the performance of an individual industry.

3.1. Empirical approach and baseline estimation equation

Our approach is to look at local average wage rates, rather than the wage rate prevailing in a city's specific industry. By observing the local average wage rate, we assume that (from the perspective of an individual firm or industry) aggregate variation is exogenous and reflects aggregate local labor market conditions: for instance, if workers can easily switch jobs within a city, they might be attracted by better-paying jobs. Industries where wages grow slower than in the rest of the local economy will then face upward pressure on their labor costs, which undermines their competitiveness. If such a mechanism can be correctly identified, we should be able to observe that such industries reveal a relatively lower economic performance.

In order to test this mechanism empirically, we set up a simple linear model of the following form:

$$\ln y_{ict} = \beta \ln W_{ct-1} + \gamma' \mathbf{X}_{ict} + \sum \delta_{it} \mathbf{D}_{it} + \sum \delta_{ic} \mathbf{D}_{ic} + \varepsilon_{ict} \tag{1}$$

In our baseline specification, the outcome variable measures the log of output produced in city c, industry i, and year t. Alternative outcome variables measure the log of industry sales, employment, and firm population. Our estimated β is the main coefficient of interest. We expect a negative sign, if local average labor costs are adequately reflected by the average wage rate. In order to address reverse causality concerns, we include this variable with a one-year lag. We interpret $\hat{\beta}$ as the estimated average elasticity of local industry performance with respect to local average labor costs.

The term $\mathbf{X}_{ict}$ denotes a vector of control variables, which we include into our regressions to control for industry-location specific developments. We include the wage rate prevailing in a city-industry pair, w_{ict}, and the corresponding value added per employee, $vadd_{ict}$. By including these controls, we first attempt to ensure that our main variable of interest (W_{ct-1}) is not contaminated by the industry-specific wage rate of a city, but that it reflects the average wage prevailing in that industry's local economic environment. Second, we want to control for labor productivity dynamics at the city-industry level in order to capture a broad range of factors that determine the evolution of this industry.

The two summation terms in Equation (1) denote different sets of fixed effects. Industry-year fixed effects are included to account for China-wide industry dynamics, which may reflect, among other things, industry-specific demand shocks or changes in production technologies. The second set of fixed effects are included to allow for city-industry specific intercepts. We thereby control for time-invariant cross-regional differences in sectoral productivity and specialization.

3.2. Identification and alternative specifications

In order to support a causal interpretation of the relationship, we use instrumental variables (IVs) and implement them in a two-stage least squares (2SLS) estimation framework. In selecting our instruments, we attempt to isolate the variation in average wage rates that can be attributed to changes of the local economic environment, which, however, cannot be immediately related to the performance of individual industries. We focus on three different mechanisms, which may have jointly affected the development of aggregate wage levels in Chinese cities.

3.2.1. Privatization of the state-owned sector

First, we consider the gradual privatization of China's economy and compute, for each city, the fraction of total firms that can be classified as state-owned or state-controlled. We refer to such firms as state-owned enterprises (SOEs) and identify an SOE whenever the combined state- or collectively-owned share of its paid-in capital amounts to 50 percent or higher. Previous studies suggest that the presence of state-owned firms is associated with local protectionism, which undermines economic development and the activities of private enterprises (Lu and Tao, 2009; Bai et al., 2009). Also their compensation schemes typically rely less on productivity than in privately managed firms, and productivity is generally lower (Driffield and Du, 2007). Consequently, we expect that the expansion of the private sector in China will induce substantial rises in local average wage levels, as returns to education increase (Li et al., 2012). Industries that cannot keep up to these adjustments might face upward pressure on their production costs and experience a relative decline in their performance.

3.2.2. Labor supply

Second, we consider instruments that shall capture developments on the supply side of the labor market. On the one hand, these might be determined by demographic factors, such as the age structure of the local resident population. While we cannot observe such data directly, we proxy for demography using the number of students enrolled in primary education.[12] In contrast to enrolment in higher education, we believe that primary school students are more likely to live with their parents (in the same city) who in turn supply

[12] We obtained this data from various editions of the *China City Statistical Yearbook*.

to the local labor market. Changes in the number of students can then be used as a rough approximation for the overall age structure in a city. We expect that increases in the number of students are negatively related to the local average wage rate. In addition to this, we attempt to proxy local labor market conditions with observations of policy documents that promote measures to attract qualified labor. We conducted an online search for official city- and province-level policy documents that mention the keyword "attract talent", in each year of our sample and reaching back to 1997.[13] Counting the number of such documents at the city level for the years 1997-2000, we interact this measure with a linear time trend and expect that cities promoting such measures since these early years, have experienced comparatively fewer labor shortages and slower wage growth during our sample period.

3.2.3. Minimum wage reform

Finally, we consider an instrument that relates to a specific policy intervention. In 2004, the Chinese central government tightened the law for the regulation and implementation of minimum wages. In particular, this required more frequent realignment to local aggregate conditions and higher penalties for firms that violate the minimum wage standard. The effects of this minimum wage reform have been recently studied by Gan et al. (2016) and Mayneris et al. (2018). A convenient feature of the minimum wage data is that levels appear to differ across cities, but that they are set for clusters of cities which do not necessarily belong to the same province. Hence, minimum wages seem to be set according to certain threshold intervals, so that cities within the same minimum wage interval do not necessarily face the same economic circumstances. One potential problem with this measure, however, is that many firms might already pay wages above the minimum wage, so that they are not affected by the reform. We therefore adopt an approach that is similar to Mayneris et al. (2018) and compute for each city the fraction of firms that paid wages below the prevailing minimum rate during two years before the reform. We then interact this cross-sectional variable with a dummy variable, which switches from zero to one in the years 2004 and after. Cities where more firms paid below the minimum wage are expected to be more exposed to the reform, and consequently experience a faster increase in the local average wage level.

3.3. Main findings

In Table 3 we report our first set of results for industry-level output, using the full sample of Chinese cities. Columns (1) and (2) report the standard OLS results. They suggest a negative and statistically significant relationship between the average local wage rate and industry production. The precision of the estimate is increased when we include the lagged industry wage rate as an additional control variable. The size of the coefficient suggests that a 10 percent increase in local average wage rates lowers industry output by about 0.8-1.2 percent. If we look at the average increase of local wage levels during our sample period, and take into account the variation explained by our control variables and fixed effects, we find that a one

[13] The online database for official documents is *Beida Fabao-Laws Regulations Chinese Database*. The URL is `http://www.pkulaw.cn/`.

standard deviation increase in local wage levels (about 11 percent) corresponds to a 0.9-1.3 percent reduction in local industry output.

Table 3: Manufacturing industry production in China and local average wages, 2000-2007

Dep. var.: log output	(1)	(2)	(3)	(4)	(5)	(6)
	OLS		2SLS – second stage			
$\ln W_{ct-1}$	-0.081^{a}	-0.121*	-2.457**	-1.544**	-0.789*	-1.323**
	(0.047)	(0.047)	(0.853)	(0.454)	(0.344)	(0.344)
$\ln vadd_{ict}$	0.565**	0.555**	0.574**	0.570**	0.568**	0.570**
	(0.011)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
$\ln w_{ict}$	0.067**	0.062**	0.114**	0.097**	0.084**	0.095**
	(0.009)	(0.011)	(0.020)	(0.013)	(0.012)	(0.012)
$\ln w_{ict-1}$		0.073**				
		(0.007)				
Observations	172,891	144,045	172,891	168,675	156,597	156,238
Clusters (city-level)	289	289	289	267	217	217
R-squared (within)	0.195	0.183				
			2SLS - first stage: $\ln W_{ct-1}$			
Fraction SOEs$_{ct-1}$			-0.229**			-0.130^{a}
			(0.065)			(0.076)
Students primary$_{ct-1}$				-0.119**		-0.069
				(0.040)		(0.044)
Policy attract labor$_{c}\times$ year$_{t}$				-0.003**		-0.002**
				(0.001)		(0.001)
Minimum wage reform$_{c}\times$ yr$\geq$2004					1.543**	1.083**
					(0.284)	(0.261)
Weak instruments (F-stat)			12.262	26.126	29.488	21.441
Underidentification (p-val)			0.001	0.001	0.000	0.000
Hansen J-statistic (p-val)				0.694		0.071

Standard errors in parentheses adjusted for clustering at city level. Statistical significance: ^{a} $p < 0.1$, * $p < 0.05$, ** $p < 0.01$. In all specifications, within R-squared refers to variation explained after controlling for city-industry and industry-year fixed effects.

Columns (3)-(6) report second-stage estimation results from different instrumental variable specifications. The corresponding first-stage coefficients for the instruments are reported in the lower panel of the table. All specifications pass the Kleibergen-Paap test statistics for weak instruments and under-identification. The validity of the exclusion restrictions is rejected at the ten percent level in the last column, when all four instruments are combined, but the test passes in column (4) where we consider only our instruments to proxy labor supply shifts.

Regarding the coefficients obtained from our two-stage estimation, we find that they are throughout negative and statistically significant, but differ in terms of their magnitude. This is especially evident when we compare our IV results to the OLS coefficients. This can be partly explained by the fact that instrumental variables — by construction and their very purpose — only capture part of the variation in our main variable of interest.[14] Hence, also the predicted variation of this variable might be much different than the actual variation we observe. Considering the first-stage prediction of the local average wage from column (4), we calculate that a one standard deviation increase corresponds to a 3.4 percent decrease in local industry production. The corresponding number for column (6) suggests a 3.8 percent decrease in industry production. These numbers indicate that increases in local average wage rates impose a comparatively larger obstacle for industry development, if wages are driven by factors related to the local supply of labor, privatization of SOEs, and the minimum wage reform in 2004. Altogether, the results lend support to the hypothesis that increasing labor costs may have an adverse impact on local industry development in China.

3.4. Robustness checks and further findings

3.4.1. Other outcome variables

In addition to investigating industry output, we are also interested in finding evidence for industry sales, employment, or firm population. To keep this short, we relegate the table to the Appendix, but briefly describe the results here. Table A1 reports estimation results in the same fashion as Table 3. The first two columns show OLS results, while columns (3)-(6) present the second-stage estimation for the different sets of instruments. Since we estimate the same sample and only change the dependent variable, first stage results are also the same and no longer reported.

The first panel of Table A1 shows the results for industry sales. They are very similar to industry output, which indicates a minor importance of inventories over the course of one year time intervals. Most of the output produced in one period is also sold. We find again large discrepancies between our coefficient estimates obtained from OLS and 2SLS estimations. In all cases, the IV estimation suggests a negative and statistically significant relationship. Point estimates range around -1.5 for our specification in column (4), regardless of which outcome variable is used. Using all four instruments to predict local average wage developments in column (6), we obtain point estimates ranging from -1.3 (for sales) and -1.4 (for employment and firm population, in the other two panels).

The similarity of results across our four different outcome variables suggests that the estimated relationship is quite uniform. There is no pattern that would suggest substitution of labor for other production inputs, or that only certain types of firms (i.e., very large or very small firms) drive this relationship. Yet, besides this uniformity across outcome measures, we expect some heterogeneity across different regions and industries, to which we turn next.

3.4.2. Outcomes across Chinese regions

In this subsection, we divide China broadly into two regions: coastal China and inner China. Moreover, in Section 2, we divided China into cost-quintiles, based on their average level of manufacturing sector, service sector, and minimum wages at the beginning of our sample period. Having shown that most of the high-cost

[14] Another, part of the explanation could be that instrumental variable estimation reduce measurement error, which is typically assumed to downward-bias the magnitudes of OLS coefficients.

locations reside in one of the nine highly developed and economically dominant coastal provinces, we may expect that increasing average wages have different repercussions for industry activity there than elsewhere. If wages are an important determinant of an industry's competitiveness, locations where wages are already high might experience greater adjustment pressures than those where the local economy is still catching up. To this end, wage growth in less developed and inner Chinese regions might reflect economic catch-up rather than competitiveness-impeding labor cost growth and, therefore, reveal also different empirical results for the relationship estimated above.

In Table 4 we present our results for output production in different regions, comparing first coastal and non-coastal locations, and then top-quintile versus the remaining quintiles, within coastal provinces. The results are reported for IV estimation only and consider two different sets of instruments. Columns (1)-(4) show the set which we used to proxy labor supply only, while columns (5)-(8) use the full set of instruments.

Table 4: Manufacturing industry production and local average wages in different Chinese regions, 2000-2007

Dep. var.: log output 2SLS: second stage	(1) inner China	(2) coastal China (by quintiles)	(3)	(4)	(5) inner China	(6) coastal China (by quintiles)	(7)	(8)
		all	non-top	top		all	non-top	top
$\ln W_{ct-1}$	-0.453	-1.427**	1.740	-1.817*	-0.502	-1.259**	-0.628	-0.768^a
	(0.593)	(0.526)	(1.522)	(0.738)	(0.434)	(0.384)	(1.179)	(0.422)
$\ln vadd_{ict}$	0.535**	0.608**	0.589**	0.609**	0.534**	0.606**	0.600**	0.600**
	(0.010)	(0.019)	(0.023)	(0.026)	(0.011)	(0.018)	(0.024)	(0.024)
$\ln w_{ict}$	0.078**	0.098**	0.022	0.116**	0.087**	0.091**	0.063**	0.089**
	(0.013)	(0.019)	(0.035)	(0.030)	(0.013)	(0.018)	(0.021)	(0.025)
Observations	71,018	97,518	29,201	68,044	60,771	95,308	26,967	68,044
Clusters (city-level)	182	85	38	47	136	81	34	47
First stage estimation: $\ln W_{ct-1}$								
Fraction SOE_{ct-1}					-0.034	-0.283**	-0.206	-0.233^a
					(0.117)	(0.103)	(0.206)	(0.127)
Students primary_{ct-1}	-0.101*	-0.128*	-0.012	-0.107	-0.113^a	-0.027	0.009	-0.039
	(0.050)	(0.058)	(0.105)	(0.067)	(0.068)	(0.054)	(0.121)	(0.065)
Policy attract $\text{labor}_c \times \text{year}_t$	-0.003	-0.003**	-0.009	-0.002**	-0.003	-0.002**	-0.009	-0.002**
	(0.002)	(0.001)	(0.007)	(0.001)	(0.003)	(0.001)	(0.008)	(0.001)
Minimum wage $\text{reform}_c \times \text{yr}\geq 2004$					1.007*	1.009**	-0.145	2.090**
					(0.418)	(0.309)	(0.461)	(0.483)
Weak instruments (F-stat)	4.290	17.414	0.961	12.270	3.009	15.712	0.610	19.867
Underidentification (p-val)	0.030	0.006	0.360	0.037	0.047	0.000	0.695	0.008
Hansen J-statistic (p-val)	0.005	0.562	0.950	0.468	0.023	0.367	0.057	0.277

Standard errors in parentheses adjusted for clustering at city level. Statistical significance: ^{a} $p < 0.1$, * $p < 0.05$, ** $p < 0.01$. In all specifications, city-industry and industry-year fixed effects are included.

We can see in Table 4 that if we restrict our sample to inner China, the estimated relationship obtained from our baseline specification is no longer supported. The point estimate is much smaller and also statistically insignificant in both columns (1) and (5). Columns (2) and (6) focus on locations in the coastal provinces and we obtain results that are very similar to those reported in Table 3. Also the validity of the exclusion restrictions is not rejected by the Hansen J statistic. Breaking the coastal sample further down and comparing top-quintile with other locations, we find that only for the former group a statistically significant and negative coefficient is reported.

We note that splitting up samples sacrifices some of the precision in our estimates. Yet, assessing our sub-sample results based on the consistency of the estimated signs of the coefficients, as well as the test statistics regarding strength and exclusion restrictions for our instruments, we find that the initially estimated relationship is most likely to be driven by the top-quintile locations in coastal China. Also the first-stage results of this sample appear to be most consistent with those reported for the full sample. The quantitatively smaller coefficient estimate in column (8) seems to indicate that the privatization of SOEs and the effect of the minimum wage reform in China have less uniform effects on industry output in the top-quintile locations.[15]

3.4.3. Outcomes across types of industries

Our results so far have shown empirical evidence of a negative relationship between average local wage rates and industry performance. While we find heterogeneity in this relationship across Chinese regions, we have ignored the fact that our sample still pools across industries. Yet, it is likely that not all industries reveal identical patterns, so we briefly explore this issue here.

Table 5: Manufacturing industry production and local average wages in different types of industries, 2000-2007

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	2SLS		OLS	2SLS	
		two IVs	all IVs		two IVs	all IVs
$\ln W_{ct-1}$	-0.018	-1.791*	-0.772^{a}	-0.041	-1.904*	-0.860*
	(0.044)	(0.744)	(0.416)	(0.045)	(0.741)	(0.415)
$\times$ low-skill intensity	-0.247**	-0.759**	-0.793**			
	(0.046)	(0.236)	(0.169)			
$\times$ labor intensity				-0.156*	-0.798*	-0.751*
				(0.061)	(0.337)	(0.284)
$\ln vadd_{ict}$	0.593**	0.609**	0.600**	0.593**	0.609**	0.600**
	(0.010)	(0.027)	(0.025)	(0.010)	(0.026)	(0.024)
$\ln w_{ict}$	0.072**	0.117**	0.091**	0.070**	0.114**	0.087**
	(0.014)	(0.029)	(0.025)	(0.014)	(0.030)	(0.025)
Observations	66,674	66,532	66,532	68,188	68,044	68,044
Clusters (city-level)	10,989	47	47	11,317	47	47
R-squared (within)	0.177			0.178		
Weak instruments (F-stat)		11.796	36.391		12.234	33.708
Underidentification (p-val)		0.015	0.000		0.017	0.001

Note: Table report estimates only for top-quintile coastal locations. Two IVs indicates instrument set using number of primary school students and number of policy documents indicating measures to attract labor. All IVs indicate that, in addition, fraction of SOEs and exposure to minimum wage reform were used as instruments. Standard errors in parentheses adjusted for clustering at city-level. Statistical significance: ^{a} $p < 0.1$, * $p < 0.05$, ** $p < 0.01$. In all specification, city-industry and industry-year fixed effects are included.

Table 5 shows OLS and 2SLS estimation results with industry-specific interaction terms for our main variable of interest. The sample is restricted to cities residing in coastal provinces and belonging to the top cost-quintile, as explained above. Those cities were found to be most likely to experience adverse effects of local average wage growth.

[15] As discussed above, firms already paying high wages are less likely to experience adjustment pressures from the minimum wage reform. Moreover, Mayneris et al. (2018) find that exposed firms increased labor productivity in response to tighter minimum wage regulations after 2004, so that industry output might be affected only in some industries.

In columns (1)-(3) of the table, we interact the local average wage rate with an industry-specific (time-invariant) measure of low-skill intensity. We obtained this measure from data used by Amiti and Freund (2010), which relies on information from the Indonesian manufacturing census.[16] By inverting this measure we obtain the fraction of production workers in total employment. The estimated coefficients indicate that the negative relationship with industry output is significantly more pronounced in low-skill intensive industries. In columns (4)-(6), we consider an alternative time-invariant indicator of industry characteristics. Computing, for the year 1999, the industry-specific labor share in production (i.e., total wage payments divided by total output), we find that industries using labor intensively at the beginning of our sample period experience a significantly larger reduction in output when the local average wage level increases.

Altogether, these findings confirm that wage growth has different repercussions for industries, depending on how intensively they make use of (low-skilled) labor in the production. While this result is not surprising and follows standard economic theory, we interpret this as reassuring evidence that our econometric identification strategy is valid.

4. The cost-saving diffusion of industry activity and its economic implications

In this section we explore the repercussions of wage growth for the organization of industrial production across China. We proceed in three steps by first identifying individual industries whose output production is negatively related to average local wage growth in the coastal top-quintile locations. Second, we focus on the remaining sample of Chinese cities and estimate whether such industries reveal a significantly different performance than industries that do not reveal such negative relationships. Third, we will investigate which locations are most likely to attract such industries and how they perform relative to other locations in inner China.

4.1. Effect of average wages on individual industries in high-cost locations

In order to conduct our first step of the analysis, we re-estimate our baseline estimation equation for the subsample of coastal top-quintile locations. Instead of estimating the average relationship with local wage levels, we now allow each CIC4 industry to have an individual coefficient. That is, we interact our main variable of interest $\ln W_{ct-1}$ with an industry-specific dummy. Moreover, instead of including $\ln W_{ct-1}$ directly into our estimation equation, we use its predicted value as obtained from our 2SLS specification with all four instruments. The reason to do so is that we intend to capture the variation in average wages that is driven by a broad set of local aggregate conditions. We have reported the baseline result for this specification in column (8) of Table 4 and now augment it as follows (control variables and fixed effects remain the same as before):

$$\ln y_{ict} = \beta^i(\ln \hat{W}_{ct-1} \times \mathbf{D}_i) + \gamma' \mathbf{X}_{ict} + \sum \delta_{it} \mathbf{D}_{it} + \sum \delta_{ic} \mathbf{D}_{ic} + \varepsilon_{ict} \qquad (2)$$

[16]This data is disaggregated at the 6-digit level of the *Harmonized System* nomenclature (HS6). We concord this data to our 4-digit CIC industry classification using a dataset from *China Customs*, which reports both CIC and HS codes. Based on a total value and frequency ranking, we created a crosswalk to assign each HS6 product to a unique CIC4 industry code.

Estimating this equation produces 400 estimates of β^i, whereas no estimate could be obtained for four industries, due to too few observations. Whenever an estimated coefficient β^i is negative and statistically significant at the five percent level, we consider this industry as "shrinking" in coastal top-quintile locations. This classification applies to 103 industries, which means that about a quarter of the industries in our sample experience a significant relative reduction of output.

An aggregated overview of these industries is presented in Table A2. It states the absolute number of industries observed across sector groups, as well as the number and fraction of industries classified as shrinking according to our estimation. The largest fraction of shrinking industries can be found in the rubber and plastic product sectors, followed by different kinds of equipment manufacturing, and the textile, clothing, and apparel industries. Much lower fractions are reported for agricultural products industries, for instance. Inspecting some key attributes of these industries, we confirm our previous findings that the set of shrinking industries are on average less skill-intensive and more labor intensive than other industries in coastal top-quintile locations (Figure A3). We also find that shrinking industries are on average less populated by state-controlled firms and that they have a lower value-added share in production.[17]

4.2. Diffusion of industry activity to inner China

To conduct the second step of our analysis, we set up an estimation equation to inspect whether industries marked as shrinking perform differently than other industries in *inner* China. That is, we regress the log of output production using only the sample of cities which we had excluded in the previous step:

$$\ln y_{ict} = \xi(shrink_i \times year_t) + \sum \delta_{ic}\mathbf{D}_{ic} + \sum \delta_{ct}\mathbf{D}_{ct} + \mu_{ict} \qquad (3)$$

In order to identify a differential performance for these industries, we interact the industry-specific marker $shrink_i$ with a time trend. We control for city-industry effects as well as city-year effects in order to capture aggregate local trends and variation. An estimate of $\xi > 0$ will indicate that industries that experience a relative decline in coastal top-quintile locations, expand relatively faster in the rest of China.[18] Our results are presented in Table 6.

The first column suggests that there is no general relationship between output production in inner China and industries marked as shrinking in the coastal top-quintile locations. In column (2), we assume that cities which already reported activity in shrinking industries at the beginning of our sample period are more likely to attract those activities from the coast. Yet, although the point estimate increases, no general trend can be detected at conventional levels of statistical significance.[19] Finally, we allow for the possibility that the

[17] All except the latter relationships are statistically significant at the 5 percent level in a probit estimation. The relationship for value-added share in production becomes strongly statistically significant in later years of our sample (i.e., since 2004). This might suggest that firms in shrinking industries have increased their share of manufactured intermediate inputs.

[18] Although we cannot fully rule out the possibility of reverse causality in this specification, we recall that the marking of industries as shrinking is based on an IV specification, which predicted variation in average wages with aggregate local developments in coastal top-quintile locations. We argue that such developments are unlikely to be determined by industry dynamics in inner China.

[19] We note that clustering at the industry level reflects the most conservative approach. Clustering at the city-industry level results in a significant coefficient in column (2), while the one reported in column (1) remains insignificant.

diffusion of industry activity takes some time, and reveals only in later years of our sample. We therefore include an additional interaction with a period dummy, which takes a value equal to one in years 2004 and after, and zero otherwise. These results, shown in columns (3)-(6), suggest that activity in the marked industries increased significantly relative to the rest of the local manufacturing sector.[20]

Table 6: Attraction of industry activity by inner Chinese locations, 1999-2007

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.: see column headings	(log) Output			Sales	Employment	Firms
$shrink_i \times year_t$	0.008					
	(0.009)					
$shrink_i \times$ coverage$_c^{99} \times year_t$		0.038	-0.004	-0.005	-0.014	0.020
		(0.028)	(0.026)	(0.027)	(0.027)	(0.019)
$shrink_i \times$ coverage$_c^{99} \times$ yr≥2004			0.261*	0.277*	0.250*	0.151^a
			(0.123)	(0.123)	(0.112)	(0.086)
Observations	116,495	115,128	115,128	115,128	115,128	115,128
Cluster (industry-level)	403	403	403	403	403	403
R-squared	0.816	0.815	0.815	0.816	0.799	0.795

Note: Standard errors in parentheses adjusted for clustering at industry level. Statistical significance: ^{a} $p < 0.1$, * $p < 0.05$, ** $p < 0.01$. All estimates include city-industry and city-year fixed effects.

In order to interpret the quantitative meaning of the results reported in the final four columns of Table 6, we multiply the point estimates with an average city's value of $coverage_c^{99}$. It measures the fraction of the total number of industries marked as shrinking that were also active in inner China's city c in 1999. In an average city this fraction was about 0.12, so that we can infer from column (3) that these industries expanded by about ($0.12 \times 0.261 \approx$) 3 percent, on average, relative to other industries since 2004. The corresponding numbers for industry sales and employment range in similar orders of magnitude, whereas the percentage increase in the number of firms is statistically weaker and estimated to be about 1.8 percent.[21]

4.3. Diffusion of industry activity to individual cities

Our results from the previous subsection suggests that industry activity might have gradually diffused from coastal top-quintile locations to other locations in China. Yet, we do not know which cities these are, and whether the diffusion promotes or inhibits their economic performance and development. We explore these questions in the following paragraphs.

4.3.1. Identification of attractive cities

In order to answer the question to which cities industry activity potentially diffuses, we adopt a generic approach similar to the one used before to identify the set of shrinking industries. That is, we augment

[20] We present a robustness check for these results in Table A3, where we explore whether our results are driven by general trends in skill- or labor-intensive industries. In both cases this cannot be confirmed.

[21] We attribute this divergence to the fact that the number of firms operating in a region not necessarily reflects its economic size. In the following, we focus mainly on the three other outcome variables.

Equation (3) by including an additional interaction term:

$$\ln y_{ict} = \xi^0(shrink_i \times year_t) + \xi^c(shrink_i \times \mathbf{Y}_{t\geq 2004} \times \mathbf{D}_c) + \sum \delta_{ic}\mathbf{D}_{ic} + \sum \delta_{ct}\mathbf{D}_{ct} + \nu_{ict} \qquad (4)$$

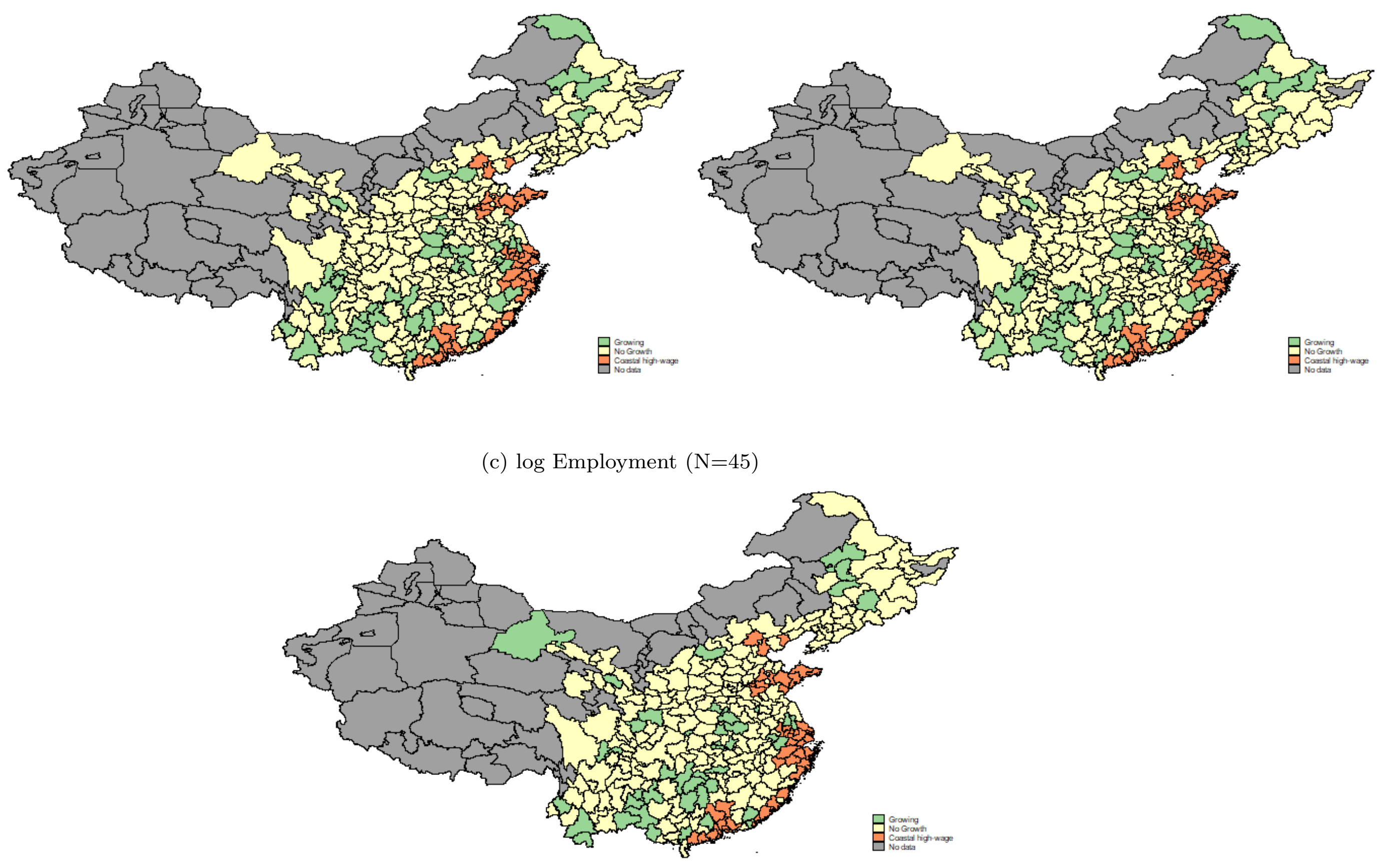
The coefficient ξ^0 is equivalent to ξ in the previous equation and capture the trend for industries marked as shrinking. The newly inserted interaction term captures the city-specific change in these industries since 2004. For any city where $\hat{\xi}^c$ is positively and significantly different from zero, we may assume that it attracts industries marked as shrinking from coastal top-quintile locations.

Figure 2: Chinese cities attracting industry activity, different metrics

(a) log Output (N=47)

(b) log Sales (N=50)

(c) log Employment (N=45)



Note: The above figures report estimation results obtained from Eq. (4). Green areas: cities attract industry activity; yellow areas: cities do not attract industry activity; red areas: coastal top-quintile locations (excluded from estimation); grey areas: no data/regions excluded from this study. N indicates the number of green areas.

We present our results graphically for three different outcome variables in Figure 2, based on a threshold of 10 percent statistical significance. "Attractive" cities are indicated by the green shading, whereas yellow shading indicates that cities did not produce a significantly positive estimate of ξ^c. Comparing the patterns across our outcome variables, displayed in panels (a)-(c), we note that they are not entirely uniform. Yet, we observe some regional clusters mainly in the southern and central regions of China. In some cases also cities in northeastern China appear to expand activity in these industries. Overall, for each outcome variable about 45-50 cities (out of 242 in our sample) expand in activities that experience a relative decline in China's high-cost locations.

Before investigating the relative performance of attractive *vis-à-vis* other cities in inner China, we present a brief summary of their key characteristics in appendix Table A4. We see in column (1) the total number of cities in four major geographic regions. Column (2) indicates the number of cities for which we obtained a significantly positive estimate of ξ^c for all three of our outcome variables. This is the case in 31 cities overall. Column (3) denotes the respective fraction, obtained from dividing column (2) by (1). It indicates that both in absolute and relative terms industries appear to have diffused mostly to central and western regions. Columns (4) and (5) suggest that an average city in coastal China has a more diversified industry base than its counterparts in other regions. It is also more active in industries marked as shrinking. Nevertheless, coastal cities are not generally more successful in attracting such industries. In the final two columns, (6) and (7), we report relative wages across industries and within cities. Computing the ratio of average wages paid in $shink_i = 1$ to $shink_i = 0$ industries, for each city and year, and comparing these ratios across cities based on whether they were found to attract industries or not, suggests that relative wages tended to be lower in the former group. The pattern is especially evident in the central and western regions and suggests that they might attract industries because of lower relative wages, i.e., greater abundance of the labor and skills needed for their production.[22]

4.3.2. Diffusion of industry activity and economic complexity

Our finding that only some locations in inner China appear to have attracted industry activity enables us to inspect their relative economic performance. Relating back to Figure 1, which suggested that some regions in inner China experienced notable increases in economic complexity, we ask ourselves whether these patterns are related to our estimates of industry attraction. To evaluate this, we estimate a linear cross-sectional regression for the change in cities' economic complexity between 1999 and 2007 ($\Delta ECI_{c,99-07}$):

$$\Delta ECI_{c,99-07} = a + b_1 ECI_{c,99} + b_2 DumGrow_c + \eta_p + e_c \tag{5}$$

The first parameter, a, denotes a constant, whereas b_1 denotes the importance of the initial level of economic complexity in city c. Our main interest lies in the parameter b_2, which will indicate whether ECIs increased faster in cities found to attract industry activity. Generally, we define a city as attractive, if its previously obtained estimates of $\hat{\xi}_c$ were positive for all three of our outcomes variables (i.e., output, sales, and employment), but we investigate also cities that are attractive in terms of each these outcome variables, separately. We include province fixed effects, η_p, to capture cross-regional heterogeneity that can be attributed to other, yet, unobserved economic and political developments. Thus, our estimate of b_2 informs about the increase in

[22]We ran linear regressions of the relative wage on a city-specific dummy indicating whether the location attracted industries or not. In the case of an attractive city, the relative wage is 4.8-6.5 percentage points lower, depending on whether no, regional, or province-level fixed effects were included. In all specifications this difference was estimated to be statistically significant at the 10 or 5 percent level.

economic complexity of cities expanding activity in $shrink_i = 1$ industries, relative other cities in the same province. Whenever we obtain a statistically significant estimate of $b_2 > 0$, we cannot reject the hypothesis that industry diffusion increases cities' economic complexity.

Our baseline results are reported in Table 7, where we consider the alternative definitions of cities' attractiveness as described above. ECIs are standardized and computed based on either cities' output or occupation structure (i.e., ECI_Y and ECI_L). We report results for our benchmark definition in the two final columns, whereas Columns (1)-(2) report the findings for cities previously found to expand in terms of industry sales, as shown in Figure 2(b). Columns (3)-(4) and (5)-(6) report findings for cities previously found to expand in terms of output and employment, respectively.

Table 7: Change of ECI for across inner Chinese cities, 1999-2007

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Attraction in:	Industry Sales		Output		Employment		All three combined	
Dep var: ΔECI	ECI_Y	ECI_L	ECI_Y	ECI_L	ECI_Y	ECI_L	ECI_Y	ECI_L
$ECI_{c,99}$	-0.370**	-0.375**	-0.369**	-0.374**	-0.368**	-0.373**	-0.365**	-0.370**
	(0.052)	(0.049)	(0.052)	(0.049)	(0.052)	(0.049)	(0.052)	(0.049)
$DumGrow_c$	0.111*	0.109*	0.115*	0.123*	0.045	0.057	0.118^{a}	0.114^{a}
	(0.054)	(0.052)	(0.056)	(0.053)	(0.061)	(0.057)	(0.067)	(0.064)
Observations	240	240	240	240	240	240	240	240
R-squared	0.367	0.399	0.367	0.401	0.360	0.393	0.365	0.397
Province FE	Y	Y	Y	Y	Y	Y	Y	Y

Note: Robust standard errors are reported in parentheses. Statistical significance: ^{a} $p < 0.1$, * $p < 0.05$, ** $p < 0.01$.

In all specifications, increases in ECIs appear to depend on the initial level of economic complexity. This indicates unconditional convergence across China and is in line with previous findings for industry production and labor productivity (Lemoine et al., 2015). Our estimates of b_2 are also significantly positive in most cases, except for cities attracting industry activity in terms of employment. An explanation could be that China's strict internal migration regulations lead to distortions in the allocation of labor and, therefore, to a less precise estimate for this outcome.[23] Another explanation could be that increases in economic complexity follow only, if industries increase actual production and sales, irrespective of employment. This might imply a transfer not only of activities but also of the related knowledge, technology, and capital so that labor productivity in these sectors increases as well.[24] Overall, a quantitative interpretation of these results suggests that cities found to attract industry activity from coastal top-quintile regions appear to have

[23] Local citizenship in China population is administered under the *hukuo* system, which distinguishes rural and urban citizenship. Due to this system, migration to a different region entails substantial impediments for the access to basic public services, such as health, insurance, or education. Recently, the *hukuo* system regulations have been reformed in some Chinese cities, which has been found to have significant impact on local labor markets (Zhao, 1999; Meng, 2012; Bosker et al., 2012). The economic costs of factor misallocation in China have been found to be substantial (Hsieh and Klenow, 2009).

[24] Recall that we found, for the later years of our sample, that industries marked as shrinking also decreased their value-added share of production in our coastal top-quintile locations. This might indicate that manufactured intermediate inputs are now sourced from inner China and from locations that are able to meet requirements to the quality of these inputs. Since we cannot observe any flows between Chinese cities, this explanation remains speculative. Yet, it fits the patterns we document here.

experienced increases in ECIs by about 0.11-0.12 standard deviations relative to other cities in the same province.

In order to see whether these estimates reflect some general (unobserved) attributes of attractive cities, we attempt to validate our findings with a placebo regression. That is, we construct city-level ECIs based on a subset of industries, selecting only those which were not marked as shrinking (i.e., $shrink_i = 0$). If attractive cities had generally higher ECI growth, estimates of b_2 should be positive and significant also in this subset. We present the results for this specification in Table A5 and find that this is not the case. We conclude that our baseline findings of faster ECI growth may indeed originate from the cost-saving diffusion of industry activity to inner China.

We are also interested in seeing whether the potential number of attracted industries matters for subsequent ECI performance. We therefore interact our indicator variable $DumGrow_c$ with the number of $shrink_i = 1$ industries in which city c is active during our sample period. For this test, we consider the most conservative classification for an attractive city, so that $DumGrow_c = 1$, if the previously city-specific estimate of $\hat{\xi}_c$ was positively significant for all three outcome variables. The results are presented in Table A6, where estimated coefficients appear to be quantitatively smaller, yet, highly statistically significant across all our specifications. This suggests that the more industries a city potentially attracts, the faster is also its ECI growth.[25] According to the point estimates reported in columns (2) and (4), each additional industry that potentially diffused to a city is associated with a 0.005 standard deviations increase in economic complexity. With an average attractive city being active in about 30 $shrink_i = 1$ industries, this implies that economic complexity increased by about 0.15 standard deviations, relative to other cities in the same province. This average estimated effect is slightly higher but still within one standard error of the corresponding point estimate from our baseline specification.

4.3.3. Diffusion of industry activity and subsequent per capita income growth

We finally ask ourselves to what extent increasing economic complexity facilitates economic development of China's local economies. To investigate this question, we first estimate the contribution of city-level ECI changes (between 1999 and 2007) to a city's growth in per capita GDP during subsequent years (between 2007 and 2014). Based on this estimate, we then compute the implied contribution of industry diffusion.

We adopt a specification similar to Hidalgo and Hausmann (2009) and Hausmann et al. (2014) to estimate the overall relationship between ECI changes and subsequent per capita GDP growth:

$$\Delta \ln PGDP_{c,07-14} = a + b_1 \ln PGDP_{c,07} + b_2 ECI_{c,99} + b_3 \Delta ECI_{c,99-07} + \eta_p + e_c \tag{6}$$

We control for the initial income level in 2007 ($\ln PGDP_{c,07}$), economic complexity in 1999 ($ECI_{c,99}$), and the change in economic complexity between 1999 and 2007, which was our dependent variable in Eq. (5).

[25] We highlight that our industry-count measure reflects only *potentially* attracted activities, because we cannot observe which (subset) of the 103 $shrink_i = 1$ industries actually do expand. Our previous estimates only indicate that this group of industries has expanded significantly faster than the group of other ($shrink_i = 0$) industries.

The results are presented in Table 8.

Table 8: Economic complexity and subsequent per capita GDP growth in Chinese cities

ECI measure:	Output-based		Occupation-based	
Dep. var.: $\Delta \ln PGDP_{c,07-14}$	(1) OLS	(2) FE	(3) OLS	(4) FE
$\ln PGDP_{c,07}$	-0.205**	-0.174**	-0.204**	-0.178**
	(0.027)	(0.032)	(0.027)	(0.031)
$ECI_{c,99}$	0.064^{a}	0.114**	0.064^{a}	0.123**
	(0.034)	(0.038)	(0.036)	(0.037)
$\Delta ECI_{c,99-07}$	0.077	0.121*	0.082	0.103^{a}
	(0.061)	(0.055)	(0.061)	(0.058)
Province FE	-	Y	-	Y
Observations	215	212	215	212
R-squared	0.162	0.370	0.163	0.371

Note: Robust Standard errors are reported in parentheses. Statistical significance: ^{a} $p < 0.1$, * $p < 0.05$, ** $p < 0.01$

Besides strong support for unconditional convergence, indicated by the negative coefficient for $\ln PGDP_{c,07}$, we also find a significant and positive relationship with economic complexity eight years before. This suggests that the growth-facilitating effect of economic complexity is quite persistent, so that an economy can benefit from it also in the medium- to long-run. Moreover, after controlling for unobserved province-level characteristics, we find for both output- and occupation-based ECIs that past increases in this measure significantly contribute to city's per capita GDP growth in later years. The quantitative interpretation is that a one standard deviation increase corresponds to a 10-12 percent increase in the growth of per capita GDP between 2007 and 2014, or about 1.4-1.7 percent per year.[26] Combining these numbers with our estimates reported in Tables 8 and A6, we calculate that the cost-saving diffusion of industries may have contributed an additional increase by about $(0.11 \times 0.103 =)$ 1.3 to $(0.15 \times 0.121 =)$ 1.8 percent to GDP per capita growth in cities that attracted industry activity.

To put these number into perspective and assess their economic magnitude, we can relate them to the actually observed increase in per capita GDP. In cities that attracted industry activity, we observe that per capita income grew by about 68% between 2007 and 2014. The contribution of cost-saving industry diffusion then amounts to approximately 1.9-2.6 percent of this growth rate. Inner Chinese cities that did not attract industry activity had about 66% per capita income growth during this period. This means that our estimated contribution of cost-saving industry diffusion to economic complexity explains between 65-90% of the difference between these cities' per capita income growth.

[26] These numbers are similar to the estimate of Hausmann et al. (2014), who find an average effect of 1.6 percent.

5. Conclusion

In this paper, we take a novel view on regional economic development in a large emerging economy. We investigate how industry restructuring in China's economically most advanced prefectural cities offers new opportunities for industry growth in less developed regions. By focusing on a specific mechanism where manufacturing industries respond to wage dynamics, induced by changes in aggregate local conditions, we find that low-skill and labor-intensive activities gradually decline in China's high-income regions. Such industries appear to expand in some of inner China's locations, where relative industry wages are comparatively low and where the distance to the coastal high-income locations is relatively small. We link these patterns to the evolution of cities' overall economic complexity and address the question whether such cost-saving diffusion of industry activity undermines or promotes the economic development of these regions. Our findings indicate that the latter is the case, and that this also transmits to an increase in the growth rate of per capita GDP in subsequent years.

Yet, while this mechanism of cost-saving industry diffusion adds to general dynamics of unconditional regional economic convergence, we find that its overall economic magnitude is limited. We attribute this to two aspects that should be borne in mind when interpreting our results. First, we analyze a relatively early time period (1999-2007). During these years, China benefited largely from its integration into the global economy, especially after its accession to the WTO and the dismantlement of trade and investment barriers. The issue of rising labor costs and the eroding competitiveness of some industries in China has likely become much more relevant in recent years, which we do not observe in our sample. Second, our data does not contain any information on transactions between Chinese cities. We adopt a consistent empirical approach to address this challenge, by first using instrumental variables to identify industries that shrink in some locations, and then investigating whether these industries expand in other locations. Nevertheless, measurement error cannot be fully ruled out. Both the early time period and potential measurement error might induce a downward bias on our estimates. We therefore interpret our results as indicative for a lower bound. Future research might address these issues and provide further insights on the validity of our findings also for other countries and time periods.

Overall, we emphasize that the "end of cheap labor", called out by commentators across academia, business, and politics does not necessarily imply a rising disadvantage for China's manufacturing sector production. To a large extent, rising wages appear to sort out the least productive and competitive industries in China's striving regions, where resources are shifted to more sophisticated economic activities. This restructuring appears to pay off as a positive externality also in the less developed regions, where such activities expand. To the extent that institutional and geographical frictions still impede the cost-saving diffusion of industry activities, policy makers may take influence to reduce them.

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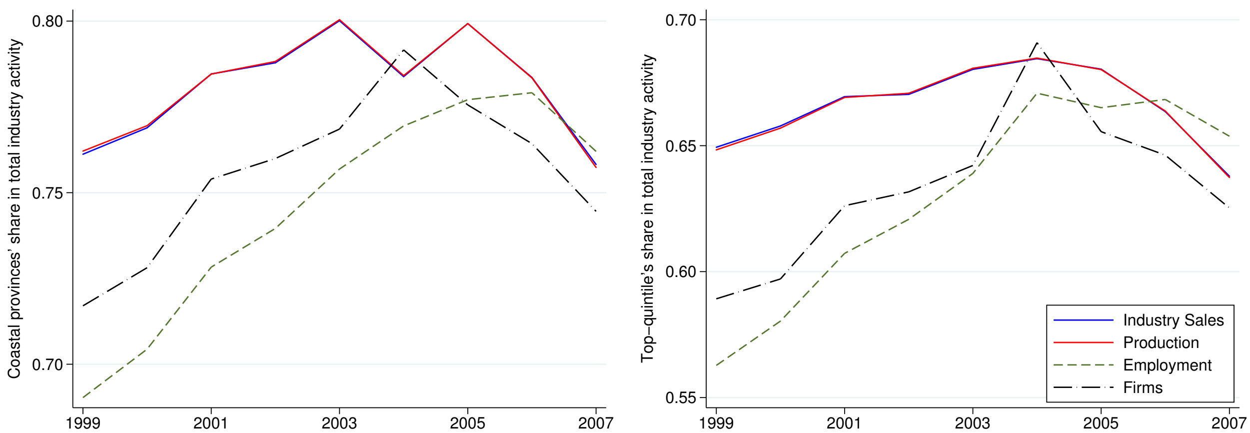
Appendix: Additional material (for online publication)

Figure A1: Contributions to overall industry activity, 1999-2007

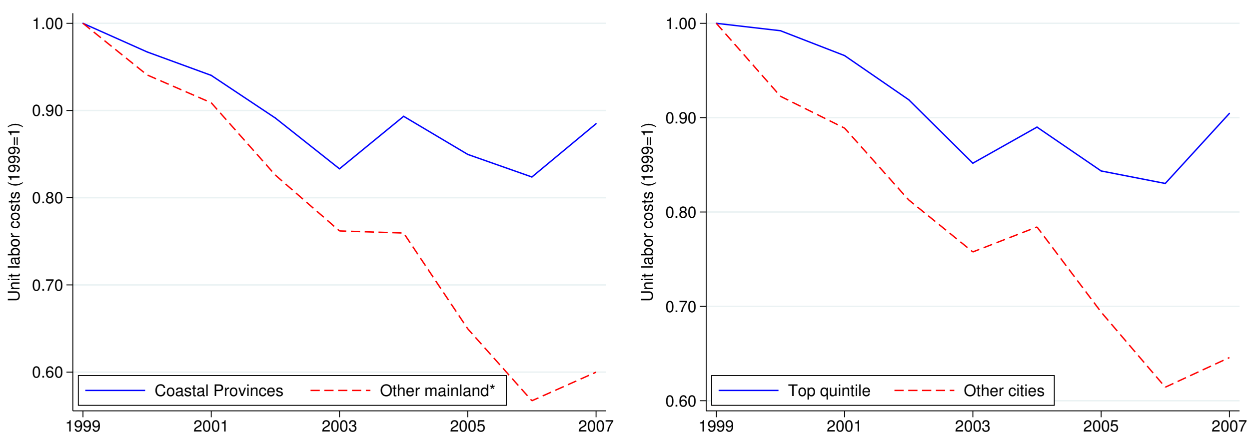
(a) Cities in coastal provinces (b) Cities in top cost quintile



Note: Authors' calculations based on Chinese firm-level data (ASIP).

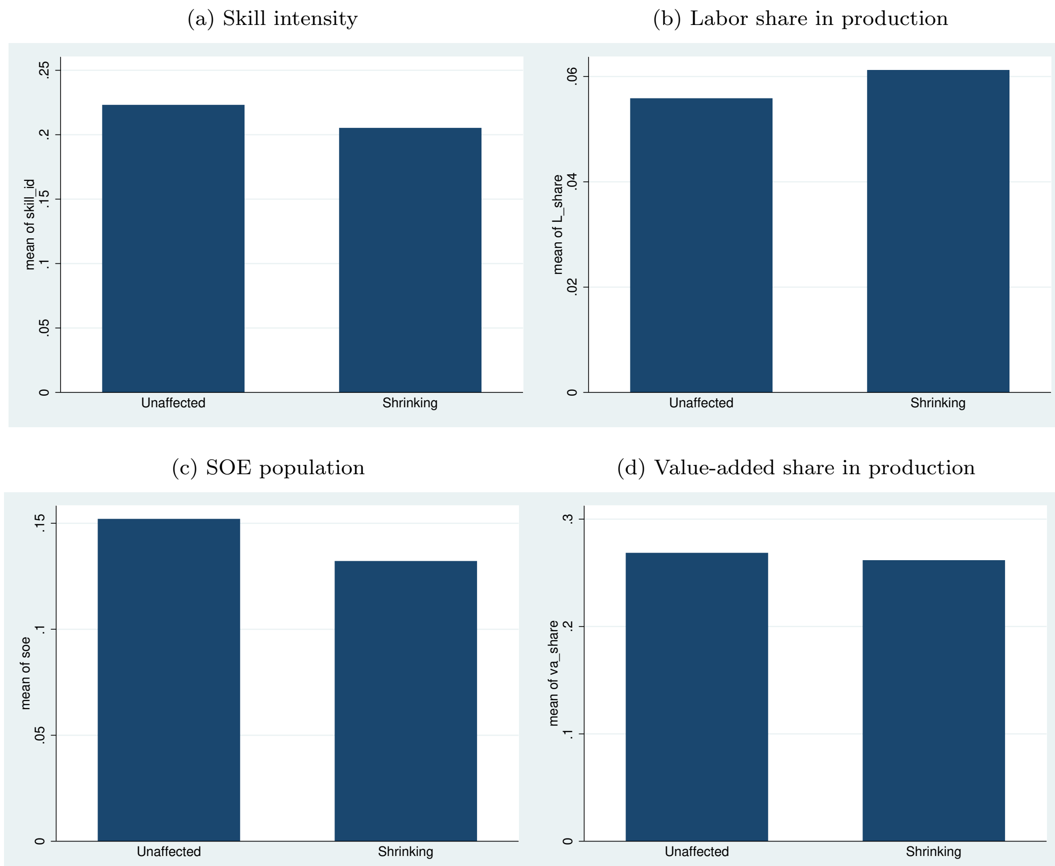
Figure A2: Unit labor costs across different Chinese regions, 1999-2007

(a) Cities in coastal provinces (b) Cities in top cost quintile



Note: Authors' calculations based on Chinese firm-level data (ASIP). Unit labor costs computed as groups' total wage bill divided by total value added.

Figure A3: Characteristics of shrinking industries in coastal top-quintile locations.



Note: Figures based on authors' calculations according to estimates obtain from Eq. (2).

Table A1: Manufacturing industry activity in China and local average wages, 2000-2007

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS		2SLS – second stage			
Dependent variable: log industry sales						
$\ln W_{ct-1}$	-0.075	-0.117*	-2.435**	-1.513**	-0.783*	-1.301**
	(0.047)	(0.048)	(0.848)	(0.454)	(0.344)	(0.343)
$\ln vadd_{ict}$	0.557**	0.546**	0.566**	0.561**	0.560**	0.562**
	(0.011)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
$\ln w_{ict}$	0.075**	0.069**	0.122**	0.104**	0.092**	0.103**
	(0.009)	(0.011)	(0.020)	(0.013)	(0.012)	(0.012)
$\ln w_{ict-1}$		0.074**				
		(0.007)				
Observations	172,891	144,045	172,891	168,675	156,597	156,238
Clusters (city-level)	289	289	289	267	217	217
R-squared (within)	0.190	0.178				
Weak instruments (F-stat)			12.262	26.126	29.488	21.441
Underidentification (p-val)			0.001	0.001	0.000	0.000
Hansen J-statistic (p-val)				0.685		0.078
Dependent variable: log industry employment						
$\ln W_{ct-1}$	-0.107*	-0.139**	-2.609**	-1.540**	-1.004**	-1.433**
	(0.046)	(0.046)	(0.873)	(0.447)	(0.330)	(0.334)
$\ln vadd_{ict}$	-0.190**	-0.195**	-0.180**	-0.185**	-0.188**	-0.186**
	(0.008)	(0.009)	(0.010)	(0.009)	(0.009)	(0.009)
$\ln w_{ict}$	-0.009	-0.011	0.041*	0.020	0.014	0.023*
	(0.009)	(0.010)	(0.020)	(0.012)	(0.011)	(0.011)
$\ln w_{ict-1}$		0.066**				
		(0.007)				
Observations	172,891	144,045	172,891	168,675	156,597	156,238
Clusters (city-level)	289	289	289	267	217	217
R-squared (within)	0.028	0.029				
Weak instruments (F-stat)			12.262	26.126	29.488	21.441
Underidentification (p-val)			0.001	0.001	0.000	0.000
Hansen J-statistic (p-val)				0.527		0.086
Dependent variable: log number of firms						
$\ln W_{ct-1}$	-0.114**	-0.124**	-2.176**	-1.454**	-1.287**	-1.447**
	(0.040)	(0.041)	(0.708)	(0.500)	(0.360)	(0.346)
$\ln vadd_{ict}$	0.030**	0.031**	0.038**	0.033**	0.034**	0.034**
	(0.005)	(0.006)	(0.007)	(0.005)	(0.006)	(0.005)
$\ln w_{ict}$	0.007	0.003	0.048**	0.033**	0.031**	0.034**
	(0.005)	(0.006)	(0.016)	(0.012)	(0.009)	(0.009)
$\ln w_{ict-1}$		0.006				
		(0.004)				
Observations	172,891	144,045	172,891	168,675	156,597	156,238
Clusters (city-level)	289	289	289	267	217	217
R-squared (within)	0.003	0.003				
Weak instruments (F-stat)			12.262	26.126	29.488	21.441
Underidentification (p-val)			0.001	0.001	0.000	0.000
Hansen J-statistic (p-val)				0.676		0.720

Standard errors in parentheses adjusted for clustering at city level. Statistical significance: ^{a} $p < 0.1$, * $p < 0.05$, ** $p < 0.01$. In all specifications, within R-squared refers to variation explained after controlling for city-industry and industry-year fixed effects.

Table A2: Sectoral overview of industries with reductions of output in coastal top-quintile locations.

CIC code	Sector	Industries	Shrinking	Fraction
29-30	Rubber and plastic products	18	6	0.33
35-41	General and special equipment (incl. transport, electrical machinery, communication and office machinery)	154	44	0.29
17-19, 24	Textile, clothing, apparel (incl. leather)	47	13	0.28
20-23	Wood and wood products (incl. paper)	23	6	0.26
31-34	Minerals and metals	59	15	0.25
25-28	Petroleum, chemicals, and products thereof	45	9	0.20
13-15	Agriculture, food, beverages	46	8	0.17
42	Crafts and other manufacturing	12	2	0.17
	Total	404	103	0.25

Note: Table reports summary statistics for number of shrinking industries, as obtained from estimating Eq. (2).

Table A3: Robustness check for attraction of industry activity by inner Chinese locations, 1999-2007

	(1) Output	(2) Sales	(3) Employment	(4) Output	(5) Sales	(6) Employment
$shrink_i \times coverage_c^{99} \times year_t$	-0.002	-0.004	-0.017	-0.002	-0.003	-0.009
	(0.026)	(0.026)	(0.028)	(0.026)	(0.027)	(0.026)
$shrink_i \times coverage_c^{99} \times$ yr$\geq$ 2004	0.298*	0.315*	0.274*	0.270*	0.284*	0.260*
	(0.125)	(0.124)	(0.114)	(0.124)	(0.123)	(0.114)
$lowskill_i \times year_t$	-0.015*	-0.014^a	0.002			
	(0.007)	(0.007)	(0.008)			
$lowskill_i \times$ yr$\geq$ 2004	-0.064*	-0.064*	-0.045^a			
	(0.027)	(0.027)	(0.027)			
$laborshare_i \times year_t$				-0.010	-0.011	-0.026**
				(0.008)	(0.008)	(0.008)
$laborshare_i \times$ yr$\geq$ 2004				-0.029	-0.026	-0.027
				(0.028)	(0.028)	(0.027)
Observations	113,522	113,522	113,522	115,020	115,020	115,020
Clusters (industry-level)	380	380	380	398	398	398
R-squared	0.815	0.815	0.798	0.815	0.816	0.799

Standard errors in parentheses adjusted for clustering at industry level. Statistical significance: ^{a} $p < 0.1$, * $p < 0.05$, ** $p < 0.01$. All estimates include city-industry and city-year effects.

Table A4: Characteristics of cities in inner China, averages 1999-2003

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Cities		Active industries		Relative wage	
Geographic Division	# total	# attractive	fraction	# total	# $shrink_i = 1$	non-growth	growth
Coastal	38	4	0.105	85	20	1.013	1.000
Center	98	16	0.163	52	12	1.019	0.940
West	71	10	0.141	31	7	1.040	0.956
Northeastern	35	1	0.029	43	10	0.971	1.031
Overall	242	31	0.128	51	12	1.016	0.956

Note: Relative wage denotes cities' average wage in industries marked $shrink_i = 1$, relative to industries marked $shrink_i = 0$. Non-growth denotes average relative wage in cities that did not attract industries after 2004, whereas growth denotes average relative wage in cities that did attract industry activity.

Table A5: Placebo: Change of ECI for Attractive Prefectural Cities

Attraction in:	Industry Sales		Industry VA		Employment		All three combined	
Dep var: ΔECI	(1) ECI_Y	(2) ECI_L	(3) ECI_Y	(4) ECI_L	(5)ECI_Y	(6) ECI_L	(7) ECI_Y	(8) ECI_L
$ECI_{c,99}$	-0.423**	-0.431**	-0.422**	-0.431**	-0.421**	-0.430**	-0.420**	-0.429**
	(0.056)	(0.053)	(0.055)	(0.053)	(0.056)	(0.053)	(0.055)	(0.053)
$DumGrow_c$	0.088	0.065	0.084	0.082	0.010	0.023	0.070	0.060
	(0.060)	(0.057)	(0.063)	(0.057)	(0.067)	(0.062)	(0.075)	(0.067)
Observations	240	240	240	240	240	240	240	240
R-squared	0.367	0.399	0.367	0.401	0.360	0.393	0.365	0.397
Province FE	Y	Y	Y	Y	Y	Y	Y	Y

Note: Robust Standard errors are reported in parentheses. Statistical significance: ^{a} $p < 0.1$, * $p < 0.05$, ** $p < 0.01$

Table A6: Change of ECI and Industry Diffusion

	(1)	(2)	(3)	(4)
Dep. var.: $\Delta ECI_{c,99-07}$	Output-based		Occupation-based	
$ECI_{c,99}$	-0.173**	-0.381**	-0.184**	-0.385**
	(0.039)	(0.052)	(0.039)	(0.049)
Num of Growing Industries	0.005**	0.005**	0.004*	0.005**
	(0.002)	(0.001)	(0.002)	(0.001)
Province FE included		Y		Y
Observations	242	240	242	240
R-squared	0.088	0.375	0.097	0.406

Note: Robust Standard errors are reported in parentheses. Statistical significance: ^{a} $p < 0.1$, * $p < 0.05$, ** $p < 0.01$