Rising Wages and Intra-country Industry Relocation: Evidence from China

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Abstract

This paper systematically examines the causal effect of rising labor cost on the reallocation of industries within China. Using panel data for the years 2004 through 2007, evolution of industries within and across Chinese prefecture-level cities is evaluated. Wage growth does not appear to impact aggregate manufacturing industry production, employment, and exports. Instead substantial restructuring shifts activity from low- to high-skill intensive industries, especially in coastal China where wages are high. Locations in inner China are able to attract some of this activity, but only under certain conditions, and to a limited amount. The findings highlight the challenges of China's industry development as wages are expected to grow further.

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1 Introduction

Only few decades after reforms towards more open economic policies began, China finds itself ranging second among the largest economies in the world. Much of this unprecedented growth experience has been attributed to low labor costs, an abundant workforce, and export-oriented policies. In recent years, however, the costs of China's most important input have been catching up, making it increasingly difficult for the country to compete with other low-wage manufacturing locations, in Asia and elsewhere. Commentators across academia, business, media, and politics increasingly call out the "end of cheap labor" in China.[1]

Rising wages — all other things equal — would be expected to lead to higher prices and threaten the competitiveness of Chinese products. In fact, Li et al. (2012) note that some sectors experienced higher wage- than productivity-growth and conclude that, relative to many other Asian economies, China is no longer a low-wage country. On the other hand, there might be reasons for manufacturing production to remain in China. As outlined in theoretical work of Grossman and Helpman (2002) and Grossman and Helpman (2005), for instance, the formation of global production networks and value chains is determined by several factors other than the unit cost of production. Knowledge of and experience with the institutional and legal environment of a production location is associated with lower search and contracting costs, whereas large populations of firms raise the probability of finding a match in a given location.[2] Through its export orientation, China has undoubtedly become part of such production networks, and may be able to defend its industries by benefiting from path dependency and its historical trade and production patterns.

Another important observation is that wage rates in manufacturing and other sectors differ greatly across locations. The most part of China's economic development was driven by soaring production and investment in regions which accommodated convenient access to sea ports. Early economic policy programs, targeted at attracting inflow of foreign direct investment (FDI) and technology, have potentially contributed to regional wage divergence by focusing on specific locations (Wang, 2013). Regions where growth rates and wages fell short of the striving regions may now have a labor cost advantage they can exploit.

Our paper analyzes the different potential paths of China's manufacturing sector evolution. In doing so, we carefully identify whether rising wages have a causal impact on China's aggregate manufacturing sector activity, and whether impacts differ across industries and regions. We also analyze to what extent — and under which conditions — regions that lagged

[1] One of the first economic research papers on this topic is Li et al. (2012). English speaking newspapers and business blogs have been reporting about this topic at least since 2006, as shown in Table A1.

[2] Grossman and Helpman (2005) label this the "thickness" of a market for production outsourcing. An empirical study by Swenson (2007) finds support for the relevance of these factors.

behind have been able to attract industry activity, due to wage growth in the economically more advanced regions. Exploiting detailed information about industrial activity at the prefecture level, for the years 2004-2007, we evaluate these questions using econometric panel data methods and instrumental variable (IV) estimation.

Our main findings suggest that rising wages negatively impact performance in China's coastal high-income regions. Relatively less skill intensive industries reveal larger quantitative wage elasticities, which is in line with standard economic theories. Lower income locations, in turn, reveal a lower responsiveness to wage growth. These patterns are found to be robust for alternative definitions of high- and low-skill industries and high- and low-wage locations.

Results for the attraction of industry activity by economically less advanced regions suggest that exports, employment, and production increase in industries where high-income regions revealed higher wage- than productivity growth. These patterns are particularly strong for less skill-intensive industries. While not all locations are equally able to attract industry activity, those located closer to the coast, and those having better infrastructure, appear to benefit the most. We interpret these findings as evidence that, besides unit labor costs, supplier and market access conditions play a decisive role for the formation of industry activity.

Our paper is one of the first to analyze the consequences of rising wages on the evolution of China's manufacturing industries. It is most closely related to recent work by Xiong and Zhang (2016) and Donaubauer and Dreger (2016). The former report a negative relationship between industry export shares and rising manufacturing wages, whereas the latter identifies a similar relationship for FDI inflows across Chinese provinces and other Asian low-income economies. While our results are consistent with theirs, we consider a different set of outcome variables and use more detailed data to identify the described patterns. Moreover, by using IV estimation techniques we are able to justify the causal interpretation of the effects. Quantification exercises suggest that about 3.5 million manufacturing jobs were lost in China's most advanced coastal locations between 2004 and 2007. Half of them were particularly low-skill intensive or exposed to export competition from other low-wage Asian countries. Of that latter number, we find that less developed regions in inner China were able to attract about 10 percent, mainly to locations nearby the developed regions.

Methodologically, the paper relates to a literature studying the allocation of different production activities by multinational firms to their subsidiaries in different regions of the world (e.g., Konings and Murphy, 2006). While we modify their specification in order to account for several identification issues arising in the context of our study, we also exploit local minimum wage developments as an exogenous source of variation from the viewpoint of a local industry. In line with other studies, we confirm that minimum wages negatively impact employment and exports, respectively, and more strongly so in less skill intensive industries (e.g. Huang et al., 2014; Gan et al., 2016), but that this effect concentrates in coastal high-income regions.

Our findings have important implications for several groups in business, society, and politics. Although the detailed sources of wage growth in China may be manifold — and of different relevance across locations — the evidence reported for a relatively early period suggests that wage pressures today should be much stronger. The competitive disadvantages arising from rapid wage growth may be compensated by relocation of activities to other Chinese regions, but the institutional framework, geography, and infrastructure are potentially important co-determinants of such adjustments. Policy-makers may take influence to reduce some of these frictions. Yet, as this paper is limited to identifying basic patterns and emphasizing the need for adjustment, further research will be useful to identify sources of wage growth and impediments to smooth adjustment.

The rest of the paper proceeds as follows. Section 2 gives a sketch of China's regional differences in economic development and wage patterns. The section also formulates the industry-level responses we expect to find across different regions and industries as labor costs increase. Section 3 describes the empirical identification strategy and details about the data sources and samples we use for its implementation. Section 4 reports the results of our econometric analyses, and discusses their robustness and quantitative implications. Section 5 concludes.

2 Stylized Patterns and Economic Intuition

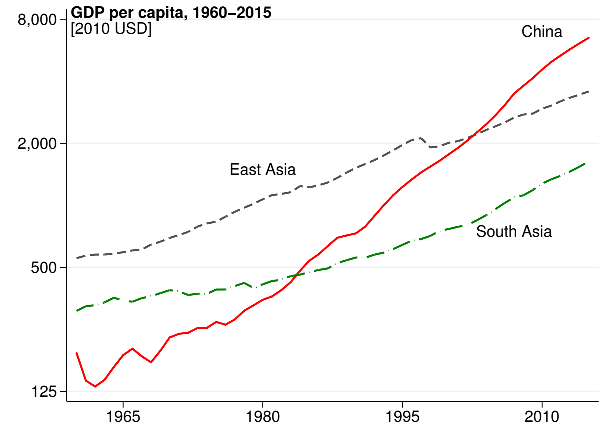
2.1 Wage disparity across China

China obtained lower-middle income status in 1998 and belongs to the higher-middle income group since 2010; together with countries like Argentina, Brazil, and Mexico, as well as many Eastern European economies.[3] Compared to many other Asian economies, Figure 1 shows that China has surpassed its developing neighbors even before. If wages are correlated with GDP per capita, the figure suggests that China's comparative advantage in labor-intensive production is no longer as strong as it used to be. Consequently, one could expect that economic activity in low-skill intensive industries declines relative to other sectors.

On the other hand, there is substantial regional disparity in wage levels across China.

[3] For a list of historical country classifications by the World Bank, see http://databank.worldbank.org/data/download/site-content/CLASS.xls

Figure 1: Per Capita Income of China and other Asian Economies, 1960-2015.



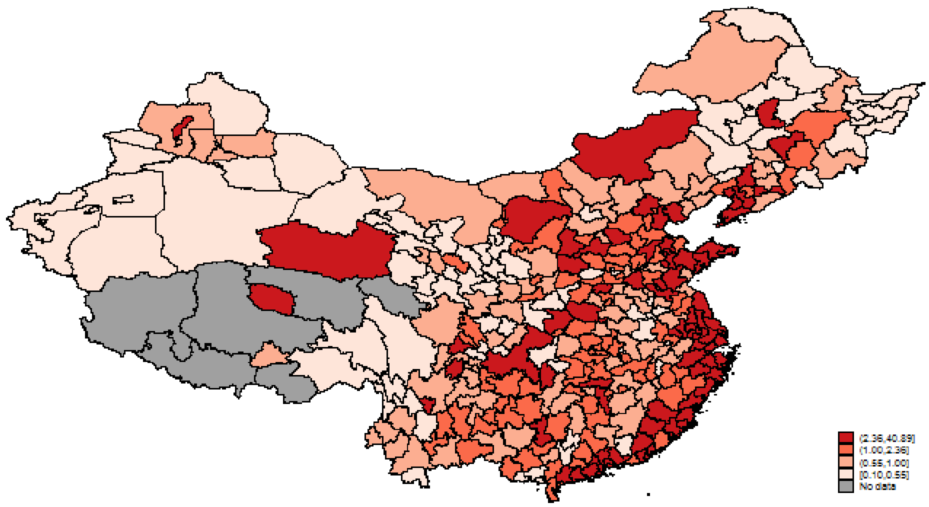
Note: Authors' calculations using data from World Development Indicators Database. *South Asia* includes Bangladesh, India, Pakistan, and Sri Lanka. *East Asia* includes Cambodia, Indonesia, Laos, Malaysia, Mongolia, Myanmar, Philippines, Thailand, and Vietnam.

According to data from its National Bureau of Statistics (NBS), in 2004, an average employee working in the cement manufacturing industry (CIC 3111) could earn about 26,000 Yuan in Zheijang's capital city, Ningbo. An average employee of the same industry in the neighboring province Anhui's capital, Hefei, however, would earn only about 7,000 Yuan — little more than an fourth. Hence, if the GDP per capita data shows than incomes ranged above those of many other Asian economies, it must be taken into consideration that actual figures are lower in some Chinese locations and higher in others. Figure 2 illustrates how firms' 2004 average annual wage and salary payments per employee in the manufacturing sector varied across prefecture-level cities. It can readily be observed that the highest manufacturing sector wages are mostly paid in locations adjacent to China's Southern and Eastern coastline. Moving from South-east China into a North-western direction, average wages tend to be lower.

2.2 Alternative Predictions from Standard Theories

Figures 1 and 2 provide ground for two alternative stories regarding China's economic development, exports, and production structure. They can be summarized in another figure characterizing comparative advantage according to classical trade theory. Figure 3 depicts a Lerner (1952) diagram with two cones of diversification. The horizontal axis denotes the amount of labor and the vertical axis depicts capital. Rays connecting the origin with any point in the diagram, hence, reflect a fixed ratio of capital to labor. Any point vertically above another, as shown by E_1 and E_2, may be read as a higher state of economic development and relatively higher abundance of capital.

Figure 2: Regional disparity in manufacturing wage levels, 2004

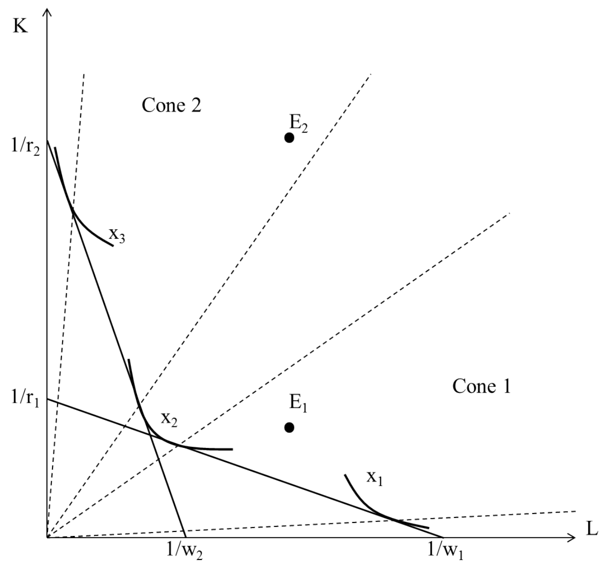


Note: Authors' calculations based on 2004 NBS firm level data, see detailed description in Section 3. Figure shows data for 331 prefecture-level cities, with the median city (Bijie, Guizhou) normalized to 1.

The diagram depicts a world economy with three goods, each requiring labor and capital to be used, but at different intensities. The least capital intensive good is called x_1 and its unit-value isoquant denotes the lower bound of the first diversification cone (Cone 1) at its tangency point with the wage-rental ratio w_1/r_1. The good x_2 denotes the cone's upper bound. x_2 also denotes the lower bound of the second cone of diversification, which has its upper bound at x_3. Looking back at Figure 1, endowment point E_1 may represent the South and East Asian economies, as well as China, at some time in the 1990s. They would export labor intensive products to the more developed economies residing in Cone 2. About two decades later, however, E_1 may no longer represent China. It has accumulated enough capital to be better reflected by E_2. As a consequence, China's production, employment, and exports of labor-intensive products would decline, whereas these activities expand in other low-income countries. The alternative story, however, imposes a condition on this prediction: only in regions where wages are high, will Chinese labor-intensive production decline, and it may expand where wages are relatively low. For the diagram this implies that E_2 represents only China's highly developed regions at the coast, whereas the more remote landlocked locations continue to reside in Cone 1. The analysis of this standard trade model entails two testable predictions.

Prediction 1. *Wage growth in China induces a decline in manufacturing exports, production, and employment in regions where wages are relatively high.*

Figure 3: Regional wage disparity in the Lerner-diagram



This follows from the conjecture that only some Chinese regions reside in Cone 2, whereas others still reside in Cone 1.

Prediction 2. *The negative impact of wage growth is concentrated in industries where labor is used intensively.*

This follows from the existence of the two cones of diversification, where moving from Cone 1 to Cone 2 entails the loss of the most labor intensive good, x_1.

Besides these classical Heckscher-Ohlin mechanics, tying factor input costs and product-specific factor utilization to the patterns of production and trade, other economic conditions are also important. For instance, Grossman and Helpman (2005) outline that search, contracting, and transportation costs play a role in the determination of a location's attractiveness for outsourced production. While moving into more remote Chinese locations is certainly associated with higher transportation costs, a functioning infrastructure and experience of foreign customers with Chinese institutions may outweigh these additional costs. Accordingly, it is possible to formulate a third prediction, i.e.,

Prediction 3. *Regions in China where wages are low attract some of the displaced activities from high-wage regions, if the former have a functioning infrastructure, and if they are not too far from high-income regions.*

In the next section we describe how these predictions are evaluated empirically, and present the data used in the empirical analysis.

3 Econometric Specifications and Data Description

3.1 Baseline Econometric Specifications

3.1.1 Wages and Industry Evolution

In order to test predictions number 1 and 2, we estimate the effect average annual wages, w_{ct}, paid in location c at time t, have on measures of Chinese manufacturing industry performance, y_{ict}. A prototype of our baseline specification is displayed in the following equation:

$$\ln y_{ict} = \alpha + \beta \ln w_{ct} + \varepsilon_{ict}. \tag{1}$$

It suggests a log-linear relationship between outcomes and the local average wage rate. The intercept is denoted by α, while any information that cannot be explained by aggregate wages is captured in a composite error term, ε_{ict}. Before discussing the structure of the error term, we first devote some space to discuss the challenges of identifying the effect of rising labor costs.

Inclusion of control variables. Standard economic theories determine wages as an equilibrium outcome of demand and supply on the labor market. Hence, the variable whose impact we seek to identify is actually an endogenous outcome of the interplay between multiple factors that rotate, shift, stretch, or skew their curves. Our aim is, as shown in the previous section, to capture the decline in the relative supply of labor, which should induce an increase of aggregate wage rates. Assuming that this effect can be correctly identified, we should observe a negative correlation between wages and industry performance measures, such as exports, production, or employment.

Yet, other factors correlated with both aggregate wages and industry outcomes could bias the actual result, unless they are properly controlled for. First, besides the relative decline in labor supply there may be improvements in the productivity of labor. This would imply both higher wages and higher production and exports, while employment would decline. Regarding the identification of our wage effect, the consequence would be that $|\hat{\beta}|$ is biased downwards, for production and exports, and that it overstates the actual effect, in the case of employment. By including measured value-added per employee into our estimation equation, we attempt to mitigate this potential source of bias.

A second source of bias could be an external demand shock. In this case wages would rise as well, because the increased demand for output or exports entails a temporary shortage of labor which is, however, cyclical rather than structural. If this occurs, production, exports, and employment would be expected to increase and, again, impose a downward bias on the estimated absolute coefficient we are willing to identify. To alleviate this concern we include the actual industry-level wage rate in location c as an additional control variable, so that β captures the effect of average wages of all local industries, excluding that of industry i which is controlled for separately.

Exploitation of subsample information and variation over time. Our detailed firm-level panel data allows us to exploit two additional strategies in addressing concerns of reverse causality. First, we make use of the firms' ownership information in order to obtain impact and outcome variables based of different subsets of the data. The impact variable w_{ct} is computed as the ratio of aggregate payrolls to aggregate employment by all firms in an industry-location year. In a second step, we compute the local wage as a weighted average of industry wages, where the initial share of industry i in c's total manufacturing employment, ω_{ic0}, is applied as a constant weight:

$$\tilde{w}_{ct} \equiv \sum_i \omega_{ic0} \frac{W_{ict}}{L_{ict}}. \tag{2}$$

Keeping industry weights constant prevents that variation in aggregate wages is actually driven by compositional change in the industry structure, which would induce an upward bias on our estimates, due to reverse causality. By lagging our impact variable by one period, and by constructing our remaining control and dependent variables based on non-state owned firms subsamples only, we seek to achieve additional exogeneity in the variation of $\tilde{w}_{ct}$.[4]

Baseline specification. After addressing these several precautionary measures, we obtain the following baseline estimation equation for our analysis of industry evolution:

$$\ln y_{ict} = \alpha + \beta \ln \tilde{w}_{rt-1} + \gamma_1 \ln va_{irt} + \gamma_2 \ln w_{irt-1} + \mu_t + \mu_i + \mu_c + \nu_{ict}. \tag{3}$$

The transformed local wage rate is expected to exhibit a negative impact on outcomes, i.e. $\hat{\beta} < 0$. The estimated coefficient for value added should depend on the outcome variable. It should be $\hat{\gamma}_1 > 0$ for exports and production, but $\hat{\gamma}_1 < 0$ for employment. As local industry wages are included to capture specific demand shocks, we expect its coefficient estimate to be positive for all outcomes, $\hat{\gamma}_2 > 0$. In addition to the control variables, dummies are

[4]The survey data allows us to identify state-owned enterprises based on the declared ownership status (e.g. state- or collectively-owned), and by non-zero equity shares held by public or collective bodies.

included to capture (i) aggregate annual fluctuations affecting China's entire manufacturing sector, μ_t, (ii) country-wide time-invariant differences in levels across industries, μ_i, and (iii) time-invariant differences in levels across locations, μ_c. In particular the location-fixed effects ensure that $\hat{\beta}$ states the estimated relationship between wages and outcomes *within* an average Chinese location.

3.1.2 Wages and Industry Attraction

The third prediction stated in Section 2 suggests that, as only parts of China experienced substantial wage growth, regions that fell behind could expand in activities that are no longer competitive in their initial location. To identify such an effect we augment our baseline specification of Eq. (3) by adding a measure of excess wage growth at the industry level:

$$\ln y_{ict} = \alpha + \xi gap_{it}^{H} + \beta \ln \tilde{w}_{rt-1} + \gamma_1 \ln va_{irt} + \gamma_2 \ln w_{irt} + \mu_t + \mu_i + \mu_c + \nu_{ict}. \tag{4}$$

The excess wage growth is measured as the log-difference between average industry-level wages and value-added per employee in region H, i.e., $gap_{it}^{H} \equiv \ln w_{it}^{H} - \ln va_{it}^{H}$. Region H is constituted of a subset of locations $h \in \Omega_H$, which are considered as high-wage locations and will be excluded from the estimation sample, i.e., $h \neq c$. As argued by Li et al. (2012), industries with faster wage than productivity growth should loose competitiveness *vis-à-vis* other low-wage locations. If this includes also regions inside China, we would expect that the estimated coefficient takes a value $\hat{\xi} > 0$.

The baseline specifications presented in this subsection will be subject to several modifications, which we will explain together with the discussion of our results in following section. Before turning to the presentation of our econometric results, the next subsection presents details on the data and samples used to carry out the analysis.

3.2 Data used for the analysis

3.2.1 Main data sources

Our main data source is the Annual Survey of Industrial Production (ASIP) conducted by China's National Bureau of Statistics (NBS). The dataset surveys manufacturing firms with annual revenues of five million RMB. The sample size varies from 165,119 in 1998 to 336,768 in 2007, but we restrict observations for outcomes to the years 2004-2007. This is done for several reasons. First, the number of observations in the data set dramatically increases between 2003 and 2004, which can be attributed to the census year with a more careful identification of firms to be surveyed (Brandt et al., 2014). The coverage of industry activity is, thus, expected to be more complete in the years 2004 and after. The second reason is that during years before 2004, China implemented numerous reforms that potentially affected industry activity asymmetrically. Before and after WTO entry, changes included — among others — dismantling of tariffs and new export and investment licensing regulations (e.g. Zi, 2016; Bai et al., 2017). While such changes may still have occurred in subsequent years, we assume that their potentially confounding impacts have been strongest in years outside our sample period.[5]

Before constructing any aggregate variables, we make efforts to identify firms' location. A location refers to a prefecture-level city, which can typically be identified by a four-digit code, but may be subject to changes due to administrative reforms or inaccurate reporting.[6] We find almost no firms that plausibly report a change in their location over time. This conforms to observations of Brandt et al. (2014), where major restructuring of firms typically entails a new firm identifier. Overall we concentrate on Chinese mainland locations, which count 339 prefecture-level cities. Our impact variable, $\tilde{w}_{ct}$, is constructed at this level of disaggregation.

Our outcome variables have an additional dimension and distinguish 389 manufacturing industries, identified by four-digit codes of the Chinese Industry Classification (CIC). Locations-industry totals of output and employment, as well as our control variables are computed at this level of disaggregation using the China NBS dataset. Our third outcome variable, exports, uses data from China Customs. Although exports are also reported in the NBS data, we believe the Customs data to be more accurate. To use this data, we aggregate the eight-digit product-level information to match with the CIC industry codes. Unmatched industry or location codes correspond to a negligible loss of exported value information in this period.

3.2.2 Identification of subsamples and summary statistics

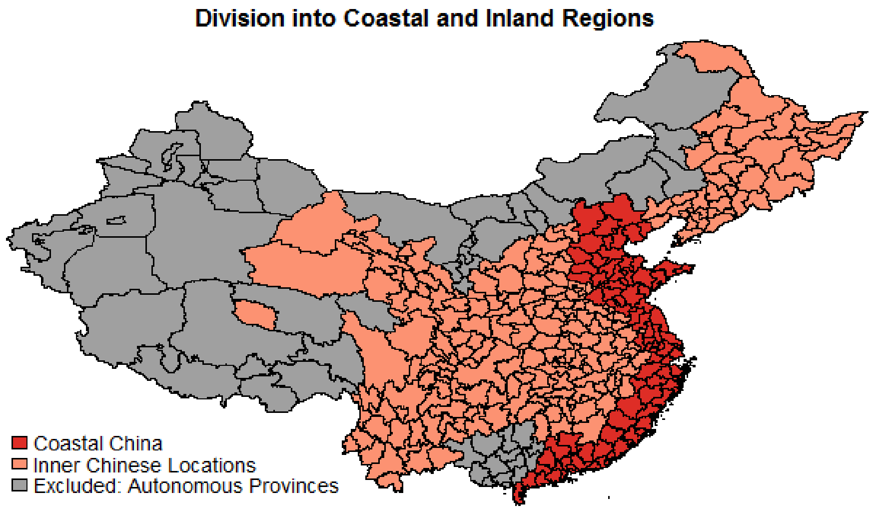
As observable in Figure 2 in Section 2, some locations have missing information for average wages in 2004. Overall, this is particularly the case in the 5 autonomous provinces of Guangxi, Inner Mongolia, Ningxia, Tibet, and Xinjiang, which together account for less than 5 percent of the total observations in our data. We therefore exclude these regions from our sample and focus only mainland locations in non-autonomous regions. We further divide our sample into two subregions, as shown in Figure 4.

The coastal areas, denoted by darker coloring, comprise nine provinces which we are going to refer to as high-wage regions in our main specifications. The inland regions with

[5] An exception could be the textiles and clothing industry, which benefitted from removal of import quotas in Europe and the US in the year 2005 (Brambilla et al., 2010; Utar, 2014; Mau, 2015).

[6] Details about our procedure are provided in the data appendix C.

Figure 4: Coastal- and inland locations of Chinese manufacturing activity.



lighter coloring identify the low-wage locations, which potentially attract activity from the coast.[7] While this distinction is seemingly crude, our summary statistics reveal that they capture the intra-country heterogeneity pretty well.

Table 1 reports relative levels and changes in average industry activity across the two subgroups, and also for the excluded autonomous provinces and Hainan island. The excluded locations appear to play a minor role in overall economic activity, accounting for at best 2.5 percent of activity in an average year. Coastal regions highlight the extreme geographical concentration of economic activity in China. 85 municipalities provide more than 90 percent of manufacturing exports, and about three quarters of output production and employment in this period. The more than twice as many inland locations provide an about equal percentage of the total observations, but fall behind in economic size.[8] The last column in the upper panel of the table shows that also average wage differences are substantial. Normalizing the average wage in coastal China to 100, those in inland locations merely amount to a fifth of it. From these numbers it is obvious, that unit production costs may differ greatly across regions.[9]

[7]Coastal provinces are Beijing, Fujian, Guangdong, Hebei, Jiangsu, Shandong, Shanghai, Tianjin, and Zhejiang. Inland provinces are Anhui, Chongqing, Gansu, Guizhou, Heilongjiang, Henan, Hubei, Hunan, Jiangxi, Jilin, Liaoning, Qinghai, Shaanxi, Shanxi, Sichuan, Yunnan.

[8]By computing these figures from the NBS firm-level data, we are aware of the possibility that small-scale industries are relatively overrepresented in inland regions, thereby understating its economic size. For the exports statistics, however, this fact should not matter. Overall, the 5 million censoring practice in the NBS-ASIP data would imply that observed expansions potentially understate actual expansion, and that observed contraction potentially overstates actual contraction.

[9]Figure B1 in Appendix B suggests that substantial wage differences exist also within these two subregions. Yet, the median coastal location's wage is still higher than the average wage in the top-quartile of the inland locations.

Table 1: Wage growth and 4-year change prefecture-level industry performance in coastal and inner China, 2004-2007.

	(1) # Locations	(2) # Obs.	(3) Exports	(4) Output	(5) Employment	(6) Wages
		% of total in an average year 2004-2007				Coast=100
Coast	85	49.2	91.1	76.3	74.8	
Inland	197	44.8	8.1	21.2	22.7	19.1
Excluded	54	6.0	0.7	2.5	2.5	8.9
		Ratio 2007 vs. 2004				
Coast		1.13	2.04	2.07	1.33	1.73
Inland		1.33	2.04	2.67	1.47	2.06
Excluded		1.36	2.70	2.59	1.36	1.78

The lower panel of Table 1 suggests that also the dynamics of industry activity differed across regions. The number of observations increased somewhat more in inner China than at the coast, which suggests that an increasing number of industries can be observed in this subsample. While exports grew at essentially the same rate, on average, columns (4) and (5) indicate that the value of production and total employment numbers increased faster in inner China. Also average wages have grown faster, which could be interpreted as lower cost pressures relative to locations where wages are already high. In our econometric analysis that follows in the next section, we investigate whether these broad patterns can be validated also statistically.

4 Results

This section presents the main results of our econometric analyses of industry evolution and industry attraction. Results of robustness checks and other information is provided in Appendix B. The first subsection focuses on the assessment of industry evolution, according to predictions 1 and 2. The second subsection examines patterns of industry attraction, as detailed in prediction 3.

4.1 Wages and industry evolution

Exports. Table 2 presents our main findings regarding the relationship between the log level of exports by industry-location year and the logged average level of the local wage in the previous year. The table is organized in two panels showing aggregate average effects and heterogeneous effects across industries, respectively.

Table 2: Exports and wages across Chinese regions and industries, 2004-2007.

	(1)	(2)	(3)	(4)	(5)
	OLS Estimation			IV Estimation	
	Pooled	Inland	Coast	Inland	Coast
Baseline & second-stage results					
Local average wage	-0.205**	-0.200**	-0.232**	1.458	-0.693*
	(0.054)	(0.076)	(0.078)	(5.677)	(0.288)
Value added	0.153**	0.118**	0.182**	0.118**	0.184**
	(0.020)	(0.026)	(0.028)	(0.039)	(0.028)
Local industry wage	0.628**	0.722**	0.551**	0.690**	0.567**
	(0.034)	(0.052)	(0.040)	(0.134)	(0.043)
Observations	79,756	28,770	50,979	26,643	50,979
Clusters	275	190	85	163	85
R-squared	0.508	0.404	0.558	0.398	0.558
Weak instrument				0.171	13.761
Underidentification				0.675	0.001
First-stage estimation results					
IV: Minimum wage				0.039	0.548**
				(0.093)	(0.148)
R-squared				0.004	0.054
Baseline & second-stage results: Industry heterogeneity					
Local average wage	-0.180**	-0.365**	-0.292**	0.943	-0.948**
	(0.055)	(0.084)	(0.067)	(3.892)	(0.234)
$\times skill_2$	-0.055	0.151*	0.071	0.339**	0.304**
	(0.034)	(0.059)	(0.048)	(0.125)	(0.070)
$\times skill_3$	0.002	0.143**	0.048^a	0.289**	0.177**
	(0.019)	(0.028)	(0.025)	(0.064)	(0.037)
$\times skill_4$	-0.018	0.078**	0.035^a	0.125**	0.132**
	(0.016)	(0.026)	(0.020)	(0.046)	(0.028)
Observations	79,756	28,770	50,979	26,643	50,979
Clusters	1,056	716	340	624	340
R-squared	0.508	0.405	0.558	0.399	0.556
Weak instrument				0.161	13.279
Underidentification				0.416	0.000

Standard errors in parentheses; statistical significance: ^{a} $p < 0.1$, * $p < 0.05$, ** $p < 0.01$. All specifications include (log) value added per employee, as control variable, as well as year, region, and industry fixed effects. Standard errors adjusted for clustering at location level (in upper panels) and location-skill-group level (in the lower panel).

The first column in the upper panel displays the estimated coefficient $\hat{\beta}$, as obtained from estimating Eq. (3) for the pooled sample, excluding autonomous provinces and the island Hainan Province as described in the previous section. Columns (2) and (3) report coefficients for the subsamples of low-wage inland regions and the coastal high-wage locations, respectively. Comparison of these coefficients suggests a fairly homogeneous negative relationship between local average wage levels and export performance. The estimated coefficients for value added per employee and for the local industry level wage rate report the expected signs. In column (4) and (5) the local average wage is assumed to be endogenous and instrumented by the local minimum wage rate. The first stage estimates at the bottom of the upper panel suggest that this wage rate can explain aggregate wage developments within coastal provinces, but that it is a relatively unreliable indicator for wage trends in inland regions. Consequently, a causal effect of wages on export performance finds stronger support in regions where wages are already relatively high, and where Prediction 1 suggested that further increases threaten the competitiveness of exports.[10]

The lower panel of Table 2 shows results of estimating an augmented model, which allows for heterogeneous patterns across industries:

$$\ln X_{ict} = \alpha + \beta_1 \ln \tilde{w}_{ct-1} + \sum_{s=2}^{S} \beta_s (\ln \tilde{w}_{ct-1} \times skill_s) + \gamma_1 \ln va_{ict} + \gamma_2 \ln w_{ict-1} + \mu_t + \mu_i + \mu_c + \nu_{ict} \tag{5}$$

As suggested in prediction 2, low-skill intensive industries should be more responsive to wage increases, because wages make up a larger portion of total production costs. Hence, we construct $S = 4$ commensurate industry-skill groups, which are based on the observed fraction of an industry's employees with reported secondary or higher education, or with specialist's qualifications.[11] $\hat{\beta}_1$ reflects the wage elasticity of exports in the least skill-intensive industries, whereas $\hat{\beta}_4$ displays the elasticity of the most skill-intensive industries, relative to the base group $s = 1$. The results reported in Table 2 broadly conform to the expected pattern. It is statistically significant and negative for the least skill-intensive industries, and less so for the higher skill groups. The IV estimates suggest, once again, that a causal effect can be observed in the coastal high-income regions. The relative size of the coefficient estimates $\hat{\beta}_2$ through $\hat{\beta}_4$ cannot confirm a monotonous relationship between skill-intensity

[10] We note that endogeneity tests cannot reject exogeneity of our instrumented variable in coastal locations. Validity of the minimum-wage instrument may be reasonably stronger, assuming that wage pressures are higher in these regions so that more firms belong to subpopulation of so-called compliers (e.g. Imbens and Angrist, 1994).

[11] Information on employment by educational background is reported in the NBS-ASIP data for the year 2004. We compute industry-level averages of these skill shares, so that we obtain a time-invariant industry-specific measure.

and wage elasticity. We are going to address this issue in our robustness checks, after assessing of our main findings for manufacturing employment and production.

Employment and Production. Table 3 displays the results for employment outcomes. The table is organized in the same way as before for exports.

Again, we find the negative correlation between local average wages and industry-level outcomes to be concentrated in the China's coastal regions. However, the instrumental variable estimation in the upper panel cannot support causality at conventional levels of significance. Yet, testing the endogeneity of our main impact variable, exogeneity of the local average wage rate cannot be rejected.[12] Looking at the lower panel of the table, the previous patterns are broadly confirmed. Less skill-intensive industries reveal a higher wage-elasticity than those using relatively more skilled labor.

Turning to Table 4, it can be observed that the results for production are extremely similar to those for employment. Both estimated size and statistical significance of point estimates for our main impact variable are close. A general decline in production due to higher wages cannot be confirmed, according to the IV results in columns (4) and (5). Yet, if any adjustment takes place it can be observed in coastal provinces. A negative causal impact on low-skill intensive production is supported by the IV regressions reported in column (5).

Overall, the main findings for industry evolution appear to be in line with our expectations, although the relationships are sometimes statistically fragile. Comparing coastal and inland regions, we expected effects to be stronger in the former subsample, because average wage levels and, hence, exposure to international low-wage competition are higher. The same holds for the relatively less skill-intensive industries. The fact that our results for exports appear to be quantitatively larger and statistically stronger may be explained by the fact that general production and employment are less exposed to international competition. As exports must compete with other countries and carry the extra burden of transportation and other costs, their adjustment to price changes may be more sensitive than that of domestic sales where transport costs are lower and where customers' preferences are presumably better understood. In addition, the functioning of market mechanisms may be expected to be stronger in international markets as compared to China's domestic economy.

4.2 Relative wages and industry attraction

In this subsection we explore evidence supporting our prediction number 3, i.e. that lower-wage inland regions in China attract industry activity from the coast. As outlined in Eq.

[12] The p-value obtained from testing against exogeneity of the instrumented variable is close to unity for the coastal regions. It ranges at 0.0525 for the non-coastal inland regions.

Table 3: Employment and wages across Chinese regions and industries, 2004-2007.

	(1)	(2)	(3)	(4)	(5)
	OLS Estimation			IV Estimation	
	Pooled	Inland	Coast	Inland	Coast
Baseline & second-stage results					
Local average wage	-0.055*	0.016	-0.147**	4.565	-0.146
	(0.027)	(0.038)	(0.036)	(15.827)	(0.164)
Value added	-0.070**	-0.111**	-0.027	-0.136*	-0.027
	(0.013)	(0.014)	(0.019)	(0.063)	(0.019)
Local industry wage	0.315**	0.317**	0.312**	0.241	0.312**
	(0.017)	(0.020)	(0.026)	(0.293)	(0.027)
Observations	112,073	50,729	61,342	46,815	61,342
Clusters	281	196	85	166	85
R-squared	0.337	0.294	0.381	0.004	0.381
Weak instrument				0.083	12.889
Underidentification				0.770	0.001
First-stage estimation results					
IV: Minimum wage				0.021	0.509**
				(0.074)	(0.142)
R-squared				0.003	0.049
Baseline & second-stage results: Industry heterogeneity					
Local average wage	0.000	-0.058[a]	-0.120**	4.407	-0.216[a]
	(0.026)	(0.030)	(0.036)	(8.236)	(0.113)
$\times skill_2$	-0.089**	0.068**	-0.051	0.149	0.060
	(0.022)	(0.022)	(0.035)	(0.213)	(0.043)
$\times skill_3$	-0.033**	0.054**	-0.026	0.126	0.043[a]
	(0.012)	(0.013)	(0.020)	(0.107)	(0.024)
$\times skill_4$	-0.021*	0.039**	0.001	0.077	0.049**
	(0.009)	(0.009)	(0.015)	(0.062)	(0.017)
Observations	112,073	50,729	61,342	46,815	61,342
Clusters	1,111	771	340	662	340
R-squared	0.338	0.294	0.381	0.003	0.380
Weak instrument				0.077	12.611
Underidentification				0.574	0.000

Standard errors in parentheses; statistical significance: ^{a} $p < 0.1$, * $p < 0.05$, ** $p < 0.01$. All specifications include (log) value added per employee, as control variable, as well as year, region, and industry fixed effects. Standard errors adjusted for clustering at location level (in upper panels) and location-skill-group level (in the lower panel).

Table 4: Production and wages across Chinese regions and industries, 2004-2007.

	(1)	(2)	(3)	(4)	(5)
	OLS Estimation			IV Estimation	
	Pooled	Inland	Coast	Inland	Coast
Baseline & second-stage results					
Local average wage	-0.034	0.017	-0.110**	5.180	-0.163
	(0.029)	(0.041)	(0.040)	(18.075)	(0.171)
Value added	0.710**	0.650**	0.771**	0.631**	0.772**
	(0.013)	(0.014)	(0.020)	(0.070)	(0.020)
Local industry wage	0.360**	0.367**	0.348**	0.281	0.350**
	(0.017)	(0.021)	(0.026)	(0.334)	(0.026)
Observations	112,073	50,729	61,342	46,815	61,342
Clusters	281	196	85	166	85
R-squared	0.466	0.442	0.485	0.159	0.485
Weak instrument				0.083	12.889
Underidentification				0.770	0.001
First-stage estimation results					
IV: Minimum wage				0.021	0.509**
				(0.074)	(0.142)
R-squared				0.003	0.049
Baseline & second-stage results: Industry heterogeneity					
Local average wage	0.018	-0.055^a	-0.083*	5.017	-0.235*
	(0.026)	(0.031)	(0.038)	(9.391)	(0.119)
$\times skill_2$	-0.082**	0.069**	-0.052	0.171	0.066
	(0.022)	(0.022)	(0.036)	(0.244)	(0.044)
$\times skill_3$	-0.032**	0.052**	-0.027	0.135	0.044^a
	(0.012)	(0.013)	(0.020)	(0.122)	(0.024)
$\times skill_4$	-0.020*	0.038**	0.002	0.079	0.050**
	(0.009)	(0.009)	(0.015)	(0.071)	(0.017)
Observations	112,073	50,729	61,342	46,815	61,342
Clusters	1,111	771	340	662	340
R-squared	0.466	0.442	0.485	0.158	0.484
Weak instrument				0.077	12.611
Underidentification				0.574	0.000

Standard errors in parentheses; statistical significance: ^{a} $p < 0.1$, * $p < 0.05$, ** $p < 0.01$. All specifications include (log) value added per employee, as control variable, as well as year, region, and industry fixed effects. Standard errors adjusted for clustering at location level (in upper panels) and location-skill-group level (in the lower panel).

(4), excess wage growth is measured by an average industry-level wage-productivity gap in coastal regions. The larger this gap, the less competitive is this industry and the more likely it should relocate to inland (or foreign) locations.

Aggregate patterns for inner China. Table 5 shows how exports, employment, and production in inner China respond to excess wage increases in coastal industries. An aggregate and uniform response cannot be detected, although exports in relatively less skill-intensive sectors seem to expand. Both results are not surprising, as inland locations themselves are heterogeneous — only some may qualify as potential new locations of economic activity — and exports have been the outcome variable that revealed to be most responsive to wage increases. General manufacturing production and employment patterns may be relatively more stable, for instance, due to administrative frictions.

Table 5: Wage-productivity gaps and attraction of industry activity, 2004-2007

	(1)	(2)	(3)	(4)	(5)	(6)
	All industries			Below-median skill intensity		
Dep. Var. (in logs)	Exports	Employment	Output	Exports	Employment	Output
Excess wage coast	0.205	-0.047	-0.022	0.366*	-0.025	0.021
	(0.138)	(0.036)	(0.035)	(0.161)	(0.059)	(0.056)
Local average wage	-0.207**	0.015	0.017	-0.328**	0.031	0.021
	(0.073)	(0.022)	(0.023)	(0.095)	(0.031)	(0.031)
Value added	0.119**	-0.111**	0.650**	0.081*	-0.192**	0.588**
	(0.028)	(0.014)	(0.014)	(0.040)	(0.020)	(0.018)
Local industry wage	0.724**	0.318**	0.367**	0.428**	0.191**	0.232**
	(0.070)	(0.022)	(0.023)	(0.062)	(0.025)	(0.027)
Observations	28,737	50,680	50,680	15,204	26,103	26,103
Clusters	374	416	416	196	209	209
R-squared	0.405	0.294	0.442	0.418	0.303	0.414

Standard errors in parentheses; statistical significance: ^{a} $p < 0.1$, * $p < 0.05$, ** $p < 0.01$. All specifications include (log) value added per worker and local wage rates, as control variables, as well as year, region, and industry fixed effects. Standard errors are adjusted for clustering at the industry level.

Attractive and less attractive locations. We next look at whether heterogeneous outcomes in industry attraction across regions are observable. If the attractiveness of a location is determined by factors in addition to local labor costs, distance to the coast (or general remoteness), the local infrastructure, and the degree of overall economic activity are plausible co-variates (e.g., Grossman and Helpman, 2005; Swenson, 2007). We test these predictions in two steps. First, we estimate location-specific coefficients for the response of our outcome variables to excess wage growth in high-income regions:

$$\ln y_{ict} = \alpha \quad + \quad \xi_c'(gap_{it}^H \times \mathbf{I}_{c\times c}) + \beta_1 \ln \tilde{w}_{ct-1} + \gamma_1 \ln va_{ict} + \gamma_2 \ln w_{ict-1} + \mu_t + \mu_i + \mu_c + \nu_{ict} \tag{6}$$

Matrix $\mathbf{I}$ has $c \times c$ dimension taking values of 1, on its diagonal, and values equal zero elsewhere. By estimating this equation, we obtain a coefficient vector $\xi_{1\times c}$, which contains the location-specific point estimates $\hat{\xi}^c$. In a second step, the point estimates are related to the location-specific characteristics mentioned above.

Figure B2 shows the distribution of the estimated coefficients for each of our three outcome variables. As suggested by the aggregate results in Table 5, point estimates are distributed around zero. The question is, however, what makes a particular location relatively more attractive? Table 6 presents results for cross-sectional OLS regressions of the point estimates on regional characteristics:

$$\hat{\xi} = a + b'\mathbf{Z} + \epsilon \tag{7}$$

The variable vector $\mathbf{Z}$ contains proxies for the attractiveness of a locations, such as distance to the coast and infrastructure.

Table 6: Determinants of industry attraction in inner China

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var. (in logs)	Exports		Employment		Production	
Avg. distance from coast	-0.483*	-0.495**	-0.245**	-0.256**	-0.266**	-0.273**
	(0.187)	(0.189)	(0.057)	(0.057)	(0.063)	(0.063)
Cum. age of SEZs	0.164*	0.183*	0.043^a	0.059*	0.018	0.029
	(0.078)	(0.086)	(0.024)	(0.026)	(0.026)	(0.028)
Avg. local wage level		-0.047		-0.041		-0.030
		(0.092)		(0.027)		(0.030)
Observations	140	140	140	140	141	141
R-squared	0.073	0.075	0.132	0.146	0.117	0.123

Standard errors in parentheses; statistical significance: ^{a} $p < 0.1$, * $p < 0.05$, ** $p < 0.01$.

Across outcome variables, the average distance from the coast appears to be the major determinant of a location's attractiveness. Although wages reveal negative signs, their level is statistically insignificant for the determination of an industry's location. For exports, distance to the coast is naturally more important, since almost all shipments will go through seaports. Another important determinant appears to be the cumulative age of

Special Economic Zones (SEZs). As documented by Wang (2013), SEZs contributed significantly to economic growth and development in the locations of their installation. Through tax holidays and other favorable treatment, they were designed to attract investment. In the context applied here, we interpret the cumulative age of SEZs in a location as a proxy for its infrastructure, assuming that increased investment and accelerated economic development entailed improvement also in communication and transport technologies, easing firms' access to markets and suppliers. Again, it appears that these factors are particularly important for export-oriented economic activities.

4.3 Robustness checks and further outcomes

While our main findings report a number of interesting and heterogeneous patterns, their robustness to alternative specifications and definitions has remained an open question. In this subsection, we review some obvious potential concerns regarding the validity of our results. As before, we first refer to our analysis of industry evolution, before we turn to assessing robustness of industry attraction. All tables and figures discussed in this subsection can be found in Appendix B.

4.3.1 Industry Evolution

Definition of high income regions. Our main findings suggest that coastal regions experience higher wage pressures, so that wage elasticity is higher there than elsewhere. Yet, we used a relatively crude measure to determine this group, by simply picking provinces located along the Southern and Eastern coastline. Our first robustness check splits this group of coastal locations into two, and compare adjustments in the upper and lower half of the wage distribution. If our wage-level argument is correct, we should observe larger adjustments in the higher-wage locations within coastal China. Table B1 confirms this pattern for both OLS and instrumental variable estimation. General negative impacts of wage growth can be observed for production and employment in those locations where wages are highest.[13]

Definition of industry skill-intensity. In Tables B2 through B4 we further distinguish adjustments according to industry characteristics. The main specification used the fraction of skilled workers in total industry employment, based on reported educational background.

[13] To put the wage differences into perspective, an average employee in the cement manufacturing industry (i.e. CIC-code 3111) in the lower-wage coastal locations earns about 71 percent of an average employee in the higher-wage locations. In inland China the percentage is somewhat lower, at roughly 65 percent. Average manufacturing wages in high-wage coastal locations, in turn, exceed average lower wage incomes by a factor of 10. This suggests that, generally, low-skilled labor is relatively scarce in the high income regions.

This may reflect local labor market conditions in China rather than industry properties (Cheng et al., 2013), and lead to inaccurate classifications of an industry's exposure to international low-wage competition. To the extent an objective industry-specific measure of relative labor intensity exists, we should be able to observe comparable adjustments for skill groups based on data from other countries. The NBER Manufacturing Productivity database provides information about the fraction of white-collar workers by NAICS industry for several years (Bartelsman and Gray, 1996). We use the updated 2006 version of this database to compute average skill intensity across US industries in the 1990s, and convert them into the CIC classifications.[14] In addition to the US data, we also use a skill intensity measure based on Indonesian data from Amiti and Freund (2010). Across all measures the results remain in line with those presented in the main tables. Least-skill intensive industries decline in response to wage growth, and causality is supported in the highest wage locations.[15] The results are also robust with regard to the non-monotony of the estimated impact as skill intensity increases. Apparently, relative factor use is not the only factor determining the intensity of labor-cost competition across Chinese industries.

Exposure to low-wage competition. While an industry's skill- or labor-intensity proxies exposure to wage competition, according to the classical theory outlined in Section 2, these characteristics may provide only an incomplete characterization. Trade costs and general tradability may vary greatly across industries, so that even if a good is low-skill intensive in its production it might be protected from international wage competition due to difficulties in its transportation between distant location. Using a more direct measure of industry's exposure to wage competition will show whether our argument in prediction 2 is correct. Table B5 shows the results for coastal locations.

In column (1), baseline results for each of our outcome variables are reported. They can be contrasted with the estimated coefficients after adding an interaction of industry i with its respective measure of competitive exposure. Exposure draws on disaggregated data from the UN Comtrade database. It measures the share of a country group in world's total imports of a particular industry. The higher the share the stronger exposure to wage competition.[16] Columns (2) through (4) suggest that exports responded negatively to wage increase, partic-

[14] We first use correspondence files from Pierce and Schott (2012) to convert data from NAICS into HS6 codes, and then apply a crosswalk we constructed from the China Customs dataset to match HS6 goods into corresponding CIC industries.

[15] Figure B3 displays the distribution of skill intensity across industries. It is remarkable that skill intensity is generally very low in the Chinese data, which emphasizes the relevance of this robustness check.

[16] The shares are based on data reported for the year 2004, and World imports encompasses imports of all countries reporting data at the 6-digit HS level. East Asia and South Asia are comprised of the same set of countries used in Figure 1, but excludes Malaysia, Mongolia, and Thailand.

ularly in industries where both East and South Asian economies have large market shares. In column (5), wages are interacted with our measure of industries' skill-intensity, as obtained from the Chinese NBS data, confirming that more skill intensive activities are relatively less negatively affected by higher wages. Yet, column (6) suggests that skill-intensity is no longer statistically significant, if exposure to low-wage Asia is included. An interpretation of this finding is that skill-intensity imperfectly proxies exposure to wage competition, whereas world import market shares of low-wage Asia are negatively correlated with skill intensity and appear to capture this effect more accurately. This pattern can broadly be observed for all outcome variables.

4.3.2 Industry Attraction

Definition of high-income regions. We can repeat our previous robustness check for industry evolution also for industry attraction. In doing so, we compute the wage-productivity gap for the top income locations of China's coastal provinces and estimate its effect on industry performance in inner China's locations. Table B6 confirms and reinforces the patterns found previously. It suggests that, generally, industry attraction cannot be observed. However, attraction of export activities in low-skill intensive industries can be confirmed. Results of interacting coastal wages, in columns (2), (4), and (6), suggest that low-wage locations in coastal provinces tend to attract more economic activity than locations in more remote provinces. Employment and production, do not appear to respond in a clear way.

Distance from the coast and other location-specific characteristics. Maintaining the definition of high-income regions of the previous paragraph, attraction of industry activity is compared across coastal low-income regions and inner Chinese locations. Estimating Eq. (6) yields 219 location-specific point estimates, for exports, and 224 coefficients for employment and production. The number of statistically significant, positive point estimates ranges between 35 (exports) and 19 (production). At least half of these effects are found among the coastal low-income regions. Table B7 presents results of a Probit estimation of the probability for a particular location to attract industry activity due to excess wage growth in coastal high-wage regions.

Column (1) in the top panel of Table B7 suggests that the probability of attracting export activity from high-income regions is higher, if the location is also in one of the coastal provinces. The same result is found for attraction of employment and production. In column (2), however, this advantage almost entirely disappears when attraction is compared between the 43 locations in coastal provinces and the 45 most proximate inland locations. The remaining columns explore what makes a location more attractive.

In the case of export activity it appears that previous export-orientation (measured by the share of exports in total production) is the most robust determinant, whereas sectoral diversification (measured by the number of 4-digit CIC industries with positive production) appears to be positively correlated with export attraction. In column (7), however, this relationship loses statistical significance. Also attraction of employment and production are dominated by the previous export-orientation of a location. Apparently, this variable summarizes the most important characteristics of a location, such as supplier- and market-access and infrastructure. In the case of attracting industry employment, sectoral specialization appears to be a relevant co-variate, and the cumulative age of SEZs, in column (5), as well as structural similarity with Asian exporters, in column (6), appear to positively covary with the likeliness to attract production activity. Loss of statistical significance in the combined specifications of column (7) might suggest that these variables are closely related and their individual effect difficult to disentangle.

4.4 Discussion and Quantifications

Our main findings suggest that wage growth in China contributes to industrial restructuring across manufacturing sectors and geographic regions. Our coefficient estimates allow us to quantify these effects to convey a clearer picture of the dimensions of sectoral restructuring.

Table 7: Counterfactual predictions for evolution and attraction of manufacturing employment, assuming constant wages in 2004-2007

Evolution of manufacturing employment in coastal China					Jobs	
Sample	$\hat{\beta}$	$\Delta \ln W_c$	$\Delta \ln L_c$	$\Delta \ln \hat{L}_c$	million	% 2007
Coast all	-0.323	0.547	0.286	0.413	-5.47	-13.5
Coast high-wage	-0.178	0.556	0.261	0.360	-3.50	-10.4
Coast high-wage, low-skill quartile	-0.193	0.565	0.184	0.293	-1.69	-11.5
Coast high-wage, high-exp. quaritle	-0.225	0.560	0.205	0.331	-1.67	-13.4
Attraction of manufacturing employment in inner China					Jobs	
Sample	$\hat{\xi}$	Δgap	$\Delta \ln L_c$	$\Delta \ln \hat{L}_c$	million	% 2007
Inland only	0.307	0.076	0.457	0.434	0.03	2.3
Inland & coast low-wage	0.439	0.104	0.531	0.485	0.12	4.4
Inland & coast low-wage, low-skill	0.863	0.104	0.486	0.397	0.17	8.6
Inland & coast low-wage, high-exp.	0.585	0.104	0.494	0.434	0.17	5.9

Note: Authors' calculations based on estimated impacts of wage growth on employment across different locations in China. $\hat{\beta}$ denotes estimated impact of local average wages on industry level employment within a location. $\hat{\xi}$ denotes weighted average of estimated impact of coastal (high-income) wage growth, net of productivity, on employment in other locations.

Table 7 shows figures for quantifications based on different subsample estimates. The upper panel considers the number of jobs "lost" in high-income regions, due to local wage growth. Depending on the specification, manufacturing industry employment in 2007 could have been between 10 and 13 percent higher had local wages not increased. According to the estimates for high-wage location in coastal China, this corresponds to roughly 3.5 million jobs. More than half of these were lost in industries residing in the bottom quartile of the skill-intensity distribution or in the top quartile of the distribution measuring industries' exposure to low-wage export competition from Asia.

The lower panel of the table suggests that attraction of manufacturing industry employment cannot fully compensate these effects. Considering job creation, due to excess wage growth in coastal high-income regions, only 27 inland or coastal low-wage locations attract employment in these industries. Weighted by the size of their manufacturing labor force in 2004, the average estimated coefficient is $\hat{\xi} = 0.439$. This implies that without wage growth in high-income regions, employment would be lower by about 115,500 jobs, which corresponds to 4.4 percent of total local employment. Focus on manufacturing attraction in low-skill or highly exposed industries suggests slightly higher absolute numbers and percentages. This is because more locations could be identified to attract such activities (the number increases to 38 and 37 locations, respectively). Comparing job destruction in coastal low-skill industries and job-creation in inner China's low-wage locations suggests that about 10 percent of the reduction in the former group's manufacturing employment is compensated by expanding activity elsewhere in China.

5 Conclusion

As China approaches the status of an upper middle income countries, concerns are raised about the viability of its low-wage and export oriented manufacturing sector. We estimated the impact higher wages have on manufacturing exports, employment, and production for the years 2004-2007. Higher local wage levels in prefecture-level cities lead to contraction of activity in all three dimensions. The relationship is particulary evident in the coastal high-income regions where wages more multiple times higher than in more remote region in inner China.

In inner China, our analysis reveals that wage growth has a weaker impact on economic activity. In fact, some locations appear to be able to attract manufacturing employment, production, and exports, as wages in high-income locations grow faster than value-added per worker. This finding is consistent with standard economic theories, but relies heavily on particular location characteristics. For instance, the likeliness to attract such activities depends on the geographic location (e.g., distance from the coast) and on the local infrastructure. Mostly, locations in the immediate neighborhood to the high-income regions appear to satisfy these criteria.

A simple quantification exercise suggests that, due to wage growth in coastal high-income regions, about 3.5 million jobs have been lost in manufacturing industries between 2004 and 2007. About half of these jobs were lost in low-skill intensive industries or in industries facing major export competition from other Asian economies at similar or lower stages of economic development. While inner Chinese region may attract some of these activities, they amount to no more than 10 percent of the losses, according to our estimates.

Yet, we find our results provide important insights. First, given that our period of analysis relates to years a decade or more ago, the wage pressures felt today are potentially much stronger than those found and presented in this paper. In this respect, it might be crucial for local firms and industries to face administrative flexibility in sourcing their inputs and choosing their location of production. Besides infrastructure, this may refer particularly to possibility of firms accessing external finance, and to the possibility of workers to choose their location of residence. Research has shown that such frictions and impediments have contributed to substantial mis-allocation and efficiency losses in the Chinese economy.

Another point worth mentioning is the need of further research to identify adjustments and dynamics at a more detailed level (of firms and workers) and for more recent years. While this is — according to our knowledge — the first paper investigating the linkages between wages, industry restructuring, and geographic disparities across China, much more can be done in future studies. In particular, it would be useful to better understand the medium- and long-run drivers of wage growth in China in order to obtain projections for future scenarios, as demographic change leads to a shrinking labor force, and as higher average educational levels further lower the supply of low-skilled labor.

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A Appendix: Additional Material

A.1 End of Cheap Chinese Labor in the Media

Table A1: The "End of Cheap Labor" in the Media

Date	Appeared in	Title
2006, March 18	New Economist Blog	China's labour pains: rising wages
2006, June 01	Harvard Business Review	The High Cost of Cheap Chinese Labor
2007, August 29	New York Times	Wages Up in China as Young Workers Grow Scarce
2010, June 10	Reuters Blog	Check Out Line: End of cheap labor in China?
2010, July 18	Economist	The end of cheap Chinese labour?
2010, July 19	Huffington Post	Chinas Cheap Labor Era Is Ending And These Products Are About To Get More Expensive
2011, June 20	DailyTech Blog	Cheap Labor in China Coming to an End
2011, June 26	Time Magazin	The End of Cheap Labor in China
2011, July 05	Time Magazin	Abandoning China: In Search of Cheap Labor, Businesses Turn to Vietnam
2012, February 17	New York Times	Chinese Labor, Cheap No More
2013, February 01	Washington Post	IMF: The era of cheap labor in China may be ending
2014, July 22	Bloomberg	Ethiopia Becomes Chinas China in Search for Cheap Labor
2014, December 02	Financial Post	What will the end of cheap Chinese labour mean for Canadians?
2015, March 12	Economist	A tightening grip
2015, April 13	LaborDish Blog	China: End of Cheap Labor Should Not Come As a Surprise
2015, May 04	Financial Times	Chinas migrant miracle nears an end as cheap labour dwindles
2016, March 17	CNN Money	Made in China' labor is not actually that cheap

A.2 Details on Minimum wages

Our OLS results are backed up by the use of minimum wages as instrumental variables. The minimum wage is guaranteed to any formally employed person in region c at time t. In contrast to the manufacturing-based wage measure, minimum wages are tied to evolve according to the changes in the cost of living in a particular location. Regions in which prices for consumption goods, housing, and other services are high, should also have higher minimum wages. Since the manufacturing sector only reflects a portion of a region's overall economic activity and aggregate conditions, the evolution of minimum wages is unlikely to be fully driven by the wage in an individual industry.

Moreover, the variation of minimum wage we exploit results from the institutional features of the reform of the minimum wage structure, in 2004. The new laws for minimum wages took effect in March 2004. They extended the minimum-wage coverage to migrate workers and dramatically increased the penalties in case of firms' failure to enforcement. The main purpose of the new minimum wage rule — as stated in official documents — was to improve the living standards.[17]

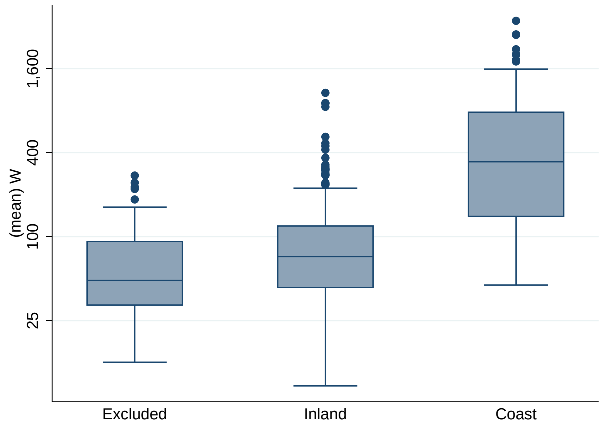
The data on local minimum wages has been collected from websites and statistical bulletins of the local governments, and is available at the city level for the years from 1998 through 2007. In total, we have 1240 minimum wage observations that cover 84.7 % of our

[17] The change in the variation of minimum wages after the 2004-reforms have been exploited also in other studies, such as (e.g. Haepp and Lin, 2016; Poncet et al., 2014).

prefecture-cities. Before using the minimum wage for our purposes we multiply monthly rates by 12 to obtain annual rates.

B Appendix: Robustness and Further Results (For Online Publication)

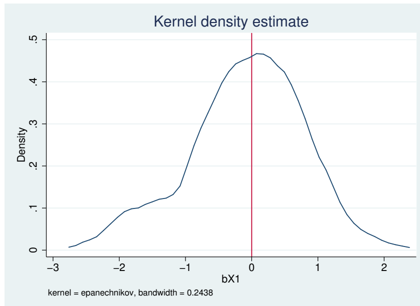
Figure B1: Wage distribution across municipalities in three Chinese subregions, 2004-2007



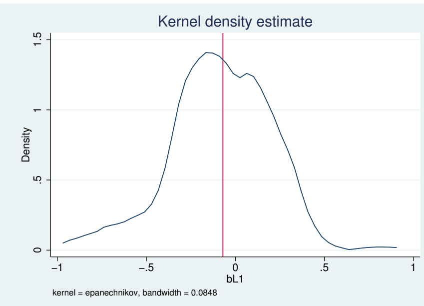
Note: Author's calculations based on NBS firm level data (see description in text). Vertical axis shows average annual wages of prefecture-level cities in respective sub-regions. The axis is scaled in logs, where labels denote average annual payment to employees in 1,000 Yuan.

Figure B2: Estimated industry attractiveness of inner Chinese locations

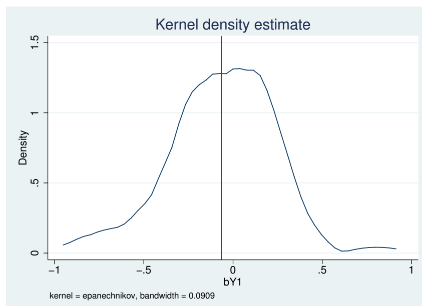
(a) Exports



(b) Employment



(c) Production



Note: Figures show kernel density estimates of 175 inner Chinese locations, for exports and employment, and of 177 locations, for production.

C Appendix: Details on Dataset Construction (For Online Publication)

This appendix presents details on the identification and harmonization of location codes. Subsections discuss procedures for alternative data sources.

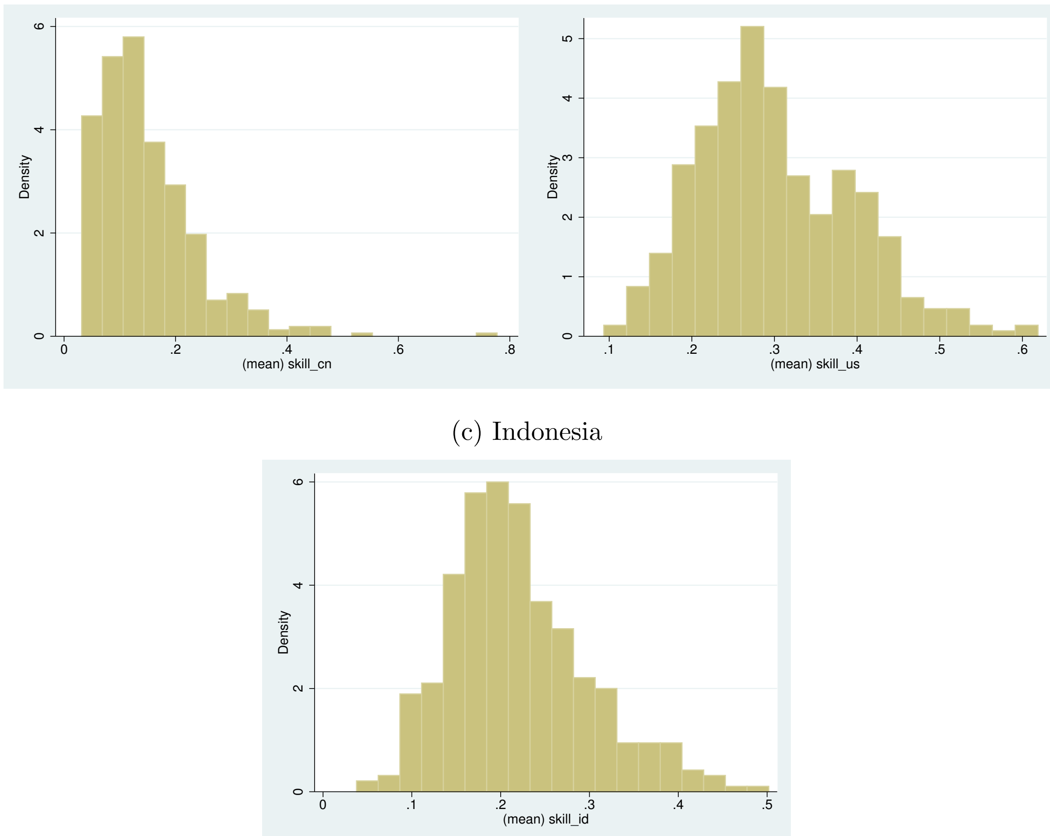
C.1 Location of firms in the NBS-ASIP panel data set

The Annual Survey of Industrial Production (ASIP) reports information about firms location based on province, zip codes, street address, phone numbers, and dq-codes. The first four digits of a dq-code identify firms location at the prefecture-level city level.

To inspect accuracy and consistency of firms location we use the firm-ID as reported for the dataset with matched information of China Customs.[18] In contrast to the firm identifiers in the original raw dataset, this ID has no more than one firm observation per year.

[18] Citation needed!

Figure B3: Distribution of measured skill-intensity across industries, in alternative countries



(a) China (b) United States

(c) Indonesia

Note: Skill-intensity measured as fraction of employees with certain educational background or occupation within industry. See text for details on the data.

General information about firms. In total, there are 527,033 enterprises reported between 1998 and 2007. Each enterprise can be followed for 1 up to 10 years. Entry and exit of firms from the dataset may result from started and discontinued business activity or from censoring at a turnover threshold of 5 million Yuan for non-state owned enterprises. The median firm can be followed for 3 years. About 24 percent of the firms appear only once in the data. 73 percent of the firms can be followed consecutively over several years, whereas 3 percent of the firms observed re-enter the dataset after being absent for one year. 40 firms re-enter after being absent for two up to four years. These numbers indicate that reporting practice of firms in the survey is relatively stable, despite substantial churning across firms.

Tracking location of firms. Our main source of information about a firms location is the prefecture-code, which we obtain from the first four digits of the dq-code reported in the data. For some firms the prefecture-code changes over time. This can be due to three reasons: (i) it could be that the firm has actually moved to a different location; (ii) the prefecture-code has changed after an administrative reform; or (iii) the information is simply inaccurate.

While the possibility that a firm has moved to a different location obviously exists, we do not believe this is the main reason for changing prefecture-codes in the data. The reason is that the firm-IDs are based on information about a firms name, zip code, phone number, and street address, among others, which contradicts a change in location. On the other hand, this implies that it is impossible to track actual geographical relocation of individual firms in the data, because such a firm will most likely have different IDs in the respective locations. We therefore focus on the other two possibilities, namely that the reported location information is inaccurate or that location codes have changed over time. This involves a more detailed inspection of 22,455 firms.

One relatively obvious source of inconsistent reporting is the stated location of a firm in one of Chinas four municipality-level provinces (i.e., Beijing, Tianjin, Shanghai, and Chongqing). While information of the 3rd and 4th digit in their prefecture-codes specifies certain districts of these cities, such details will not be required in our analyses. Hence, the last two digits will any prefecture code referring to these locations will be uniformly set zero. This step more than halves the number of firm observations with inconsistent location information.

The second step focuses on the subsample of firms with consistent province, but inconsistent prefecture code. The following rule is applied: First, a firm is assigned the prefecture-code that is reported most frequently across all its observations; second, if frequencies equal, the firm will be assigned the prefecture-level code which appears numerically first. After this step, there are only 41 firms left which report both inconsistent province and prefecture-level information over time.

It is remarkable that the inconsistency among these remaining firms is persistent: (i) no firm ever reports more than two different provinces; and (ii) once the province has changed, the firm remains in that new location. Yet, some of these inconsistencies can be attributed to inaccurate reporting practice. This results from the inspection of zip codes. Firms with consistent zip codes in the first 2 digits will not have moved to a different province, so that the prefecture-code appearing most frequently or numerically first will be assigned. For the remaining 34 enterprises, two locations will be accepted, because all of these firms also report inconsistent phone numbers, company names (except three firms), legal representatives (except one firm), and town locations. Hence, within each firm province pair, prefecture-codes are harmonized based on the frequency-and-numerical-sorting rule applied in previous steps to firms of other subsamples. After this final step, firms in 428 different prefecture-level locations can be distinguished.

Harmonization of prefecture codes. Even with consistent location information within firms it is possible that some location codes are still inaccurate. For instance, a firm consistently reporting location code 2200 states the province in which it operates but not its prefecture-level city. To identify inaccurate or outdated prefecture-codes, we map our firm-level information to the list of prefecture-codes available from the website of Statistics China.[19] In fact, 89 prefecture-codes of 7,811 firms are obtained from the ASIP data, but do not appear in the official list of prefecture cities. Again, zip code information of the firms is exploited to verify the true location of these firms.

First, focus lies on the majority of firms with consistent zip code information. At later stages, firms stating 2 or more different zip codes for are inspected. The information about the zip codes location is retrieved from the worldwide web, and by combining this information with the list of prefecture-level cities from Statistics China.[20] It is possible assign a new and unique prefecture code to most firms. After combining the updated prefecture codes with our benchmark list, only 31 firms remain as reporting unknown and unidentifiable location information. Overall, the final firm location dataset encompasses 339 locations for 527,002 enterprises reporting operations between 1998 and 2007.

C.2 Location of exports origin in the China Customs dataset

The China Custom dataset reports disaggregated exports by firm, region, product, among others. We seek to identify the location of exports origin by using the 4-digit city code. Unfortunately, these codes are not identical to those in the ASIP panel, or in the prefecture-level city list. Hence, we make use of the China-Hong Kong Trade codebook (Feenstra et al. 2016) and match city codes based on their reported name. In some regions of China, the exporting location is unspecified in a category called other. While overall, these trade flows account for less than 3 percent of the total trade between 2004 and 2007, in some regions, such as Hainan Island or in the Autonomous provinces, its share may be substantial more than 20 percent in some cases. Our analysis, however, does not include these locations, so that amount of unused information is limited.

[19] http://www.stats.gov.cn/tjsj/tjbz/xzqhdm/200307/t20030722_38300.html

[20] The website https://www.travelchinaguide.com/essential/area_zip/ and the Google search engine assist identification and allocation of zip codes to Chinese cities.

Table B1: Wage elasticity across high- and low-wage locations in coastal China, 2004-2007

	(1)	(2)	(3)	(4)	(5)	(6)
	Coast low-wage			Coast high-wage		
	Exports	Employment	Output	Exports	Employment	Output
Results of standard OLS estimation:						
Local average wage	-0.194	-0.052	0.017	-0.241*	-0.178**	-0.159*
	(0.116)	(0.057)	(0.060)	(0.106)	(0.052)	(0.062)
Value added	0.111*	-0.111**	0.705**	0.214**	0.027	0.809**
	(0.051)	(0.024)	(0.025)	(0.026)	(0.024)	(0.030)
Local industry wage	0.571**	0.262**	0.288**	0.514**	0.341**	0.387**
	(0.058)	(0.022)	(0.025)	(0.056)	(0.042)	(0.040)
Observations	16,697	22,470	22,470	34,273	38,867	38,867
Cluster (locations)	43	43	43	42	42	42
R-squared	0.416	0.327	0.485	0.616	0.429	0.507
Results of 2nd Stage IV estimation:						
Local average wage	-2.525	0.320	0.072	-0.308	-0.326*	-0.289*
	(2.606)	(0.524)	(0.551)	(0.231)	(0.136)	(0.140)
Value added	0.124*	-0.113**	0.704**	0.214**	0.028	0.810**
	(0.050)	(0.025)	(0.026)	(0.026)	(0.024)	(0.030)
Local industry wage	0.652**	0.250**	0.286**	0.516**	0.345**	0.391**
	(0.100)	(0.029)	(0.028)	(0.059)	(0.042)	(0.039)
Underidentification	0.345	0.286	0.286	0.001	0.000	0.000
Weak instrument	0.890	1.165	1.165	20.850	21.033	21.033
Results of 1st Stage IV estimation:						
Local minimum wage	0.173	0.192	0.192	0.915**	0.896**	0.896**
	(0.183)	(0.178)	(0.178)	(0.200)	(0.195)	(0.195)
Observations	16,697	22,470	22,470	34,273	38,867	38,867
Cluster (locations)	43	43	43	42	42	42

Standard errors in parentheses. Statistical significance: ^{a} $p < 0.1$, * $p < 0.05$, ** $p < 0.01$. Sample includes coastal locations only, as defined in Figure 4. Standard errors adjusted for clustering at location level. All specifications include year, industry, and location fixed effects.

Table B2: Wages and Export performance across regions and industries by skill-intensity, 2004-2007

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS estimation			IV estimation		
	Inland	Low coast	High coast	Inland	Low coast	High coast
Skill-quartiles based on China NBS data						
Local average wage	-0.365**	-0.283*	-0.377**	0.943	-3.243^a	-0.739**
	(0.084)	(0.111)	(0.098)	(3.892)	(1.821)	(0.204)
$\times skill_2$	0.151*	0.102	0.203*	0.339**	0.698*	0.576**
	(0.059)	(0.084)	(0.085)	(0.125)	(0.326)	(0.145)
$\times skill_3$	0.143**	0.075	0.121**	0.289**	0.469**	0.318**
	(0.028)	(0.047)	(0.044)	(0.064)	(0.153)	(0.071)
$\times skill_4$	0.078**	0.038	0.049	0.125**	0.330**	0.202**
	(0.026)	(0.036)	(0.035)	(0.046)	(0.106)	(0.058)
Value-added	0.119**	0.112**	0.213**	0.120**	0.133**	0.214**
	(0.025)	(0.039)	(0.026)	(0.032)	(0.040)	(0.026)
Local industry wage	0.720**	0.575**	0.510**	0.690**	0.685**	0.503**
	(0.048)	(0.062)	(0.051)	(0.097)	(0.094)	(0.053)
Observations	28,770	16,697	34,273	26,643	16,697	34,273
Cluster	716	172	168	624	172	168
R-squared	0.405	0.416	0.616	0.399	0.397	0.615
Weak Instrument				0.161	0.833	20.474
Underidentification				0.416	0.069	0.000
Skill-quartiles based on US NBER Manufacturing data						
Local average wage	-0.421**	-0.308**	-0.415**	1.159	-3.177^a	-0.766**
	(0.080)	(0.113)	(0.096)	(3.941)	(1.668)	(0.201)
$\times skill_2$	0.400**	0.152	0.314**	0.612**	0.949**	0.629**
	(0.068)	(0.095)	(0.093)	(0.146)	(0.331)	(0.138)
$\times skill_3$	0.104**	0.086^a	0.081^a	0.163*	0.382*	0.303**
	(0.036)	(0.046)	(0.043)	(0.064)	(0.158)	(0.063)
$\times skill_4$	0.108**	0.055	0.080*	0.147**	0.298**	0.227**
	(0.025)	(0.040)	(0.035)	(0.045)	(0.097)	(0.050)
Value-added	0.117**	0.113**	0.217**	0.115**	0.130**	0.218**
	(0.025)	(0.040)	(0.025)	(0.033)	(0.041)	(0.026)
Local industry wage	0.721**	0.577**	0.506**	0.687**	0.685**	0.501**
	(0.046)	(0.061)	(0.050)	(0.096)	(0.084)	(0.053)
Observations	28,724	16,686	34,195	26,598	16,686	34,195
Cluster	707	172	168	622	172	168
R-squared	0.406	0.416	0.615	0.399	0.397	0.613
Weak Instrument				0.159	0.836	20.904
Underidentification				0.418	0.069	0.000
Skill-quartiles based on Indonesian Manufacturing industry data						
Local average wage	-0.282**	-0.327*	-0.234*	1.169	-3.313^a	-0.513*
	(0.091)	(0.137)	(0.094)	(3.884)	(1.690)	(0.208)
$\times skill_2$	0.148^a	0.089	0.130	0.243^a	0.681*	0.582**
	(0.080)	(0.122)	(0.089)	(0.140)	(0.322)	(0.156)
$\times skill_3$	0.076*	0.037	-0.020	0.167*	0.526**	0.121^a
	(0.037)	(0.060)	(0.039)	(0.079)	(0.154)	(0.068)
$\times skill_4$	0.007	0.116*	-0.051	0.031	0.330**	0.019
	(0.026)	(0.045)	(0.035)	(0.058)	(0.104)	(0.056)
Value-added	0.119**	0.115**	0.217**	0.119**	0.135**	0.218**
	(0.025)	(0.041)	(0.026)	(0.031)	(0.042)	(0.027)
Local industry wage	0.723**	0.578**	0.509**	0.694**	0.670**	0.505**
	(0.046)	(0.064)	(0.048)	(0.094)	(0.093)	(0.049)
Observations	28,736	16,687	34,215	26,610	16,687	34,215
Cluster	701	172	168	618	172	168
R-squared	0.404	0.416	0.615	0.398	0.396	0.614
Weak Instrument				0.161	0.854	20.918
Underidentification				0.416	0.066	0.000

Standard errors in parentheses. Statistical significance ^{a} $p < 0.1$, * $p < 0.05$, ** $p < 0.01$. All specifications include time-, industry-, and location-fixed effects. Standard errors adjusted for clustering at location-skill group level. See text for details on data.

Table B3: Wages and Employment across regions and industries by skill-intensity, 2004-2007

	(1)	(2)	(3)	(4)	(5)	(6)
		OLS estimation			IV estimation	
	Inland	Low coast	High coast	Inland	Low coast	High coast
Skill-quartiles based on China NBS data						
Local average wage	-0.058^a	-0.045	-0.193**	4.407	0.042	-0.478**
	(0.030)	(0.056)	(0.059)	(8.236)	(0.420)	(0.109)
$\times skill_2$	0.068**	-0.032	0.020	0.149	0.296*	0.148^a
	(0.022)	(0.044)	(0.069)	(0.213)	(0.116)	(0.089)
$\times skill_3$	0.054**	-0.020	0.014	0.126	0.181**	0.112*
	(0.013)	(0.024)	(0.039)	(0.107)	(0.065)	(0.047)
$\times skill_4$	0.039**	0.020	0.003	0.077	0.138**	0.086*
	(0.009)	(0.017)	(0.027)	(0.062)	(0.039)	(0.034)
Value-added	-0.111**	-0.110**	0.027	-0.136**	-0.109**	0.028
	(0.012)	(0.019)	(0.021)	(0.035)	(0.019)	(0.021)
Local industry wage	0.317**	0.263**	0.340**	0.240	0.259**	0.339**
	(0.018)	(0.023)	(0.034)	(0.155)	(0.029)	(0.033)
Observations	50,729	22,470	38,867	46,815	22,470	38,867
Cluster	771	172	168	662	172	168
R-squared	0.294	0.327	0.429	0.003	0.320	0.427
Weak Instrument				0.077	1.130	20.843
Underidentification				0.574	0.037	0.000
Skill-quartiles based on US NBER Manufacturing data						
Local average wage	-0.036	-0.018	-0.242**	3.858	0.145	-0.584**
	(0.029)	(0.050)	(0.061)	(6.782)	(0.405)	(0.129)
$\times skill_2$	0.138**	-0.075	0.167*	0.114	0.237^a	0.425**
	(0.023)	(0.049)	(0.073)	(0.135)	(0.131)	(0.098)
$\times skill_3$	0.026*	-0.026	0.014	0.093	0.123^a	0.158**
	(0.010)	(0.019)	(0.038)	(0.073)	(0.065)	(0.047)
$\times skill_4$	0.011	-0.006	0.033	0.048	0.128**	0.120**
	(0.007)	(0.017)	(0.029)	(0.048)	(0.044)	(0.035)
Value-added	-0.109**	-0.107**	0.033^a	-0.132**	-0.108**	0.034^a
	(0.011)	(0.017)	(0.018)	(0.030)	(0.017)	(0.018)
Local industry wage	0.318**	0.263**	0.341**	0.255*	0.260**	0.341**
	(0.017)	(0.026)	(0.031)	(0.126)	(0.031)	(0.031)
Observations	49,902	22,069	37,666	46,042	22,069	37,666
Cluster	766	172	168	660	172	168
R-squared	0.293	0.323	0.422	0.071	0.316	0.419
Weak Instrument				0.088	1.095	21.017
Underidentification				0.548	0.040	0.000
Skill-quartiles based on Indonesian Manufacturing industry data						
Local average wage	-0.076*	-0.106^a	-0.137*	4.063	0.031	-0.349**
	(0.033)	(0.061)	(0.060)	(7.324)	(0.434)	(0.113)
$\times skill_2$	0.128**	0.009	0.044	0.207	0.387**	0.225*
	(0.031)	(0.060)	(0.069)	(0.168)	(0.136)	(0.098)
$\times skill_3$	0.064**	0.028	-0.023	0.128	0.238**	-0.003
	(0.014)	(0.027)	(0.034)	(0.100)	(0.069)	(0.043)
$\times skill_4$	0.031**	0.040^a	-0.054*	0.091	0.146**	-0.043
	(0.009)	(0.021)	(0.028)	(0.092)	(0.049)	(0.036)
Value-added	-0.109**	-0.107**	0.033^a	-0.133**	-0.106**	0.033^a
	(0.011)	(0.020)	(0.019)	(0.032)	(0.020)	(0.019)
Local industry wage	0.318**	0.264**	0.343**	0.249^a	0.255**	0.346**
	(0.017)	(0.024)	(0.032)	(0.139)	(0.027)	(0.032)
Observations	49,842	22,021	37,671	45,985	22,021	37,671
Cluster	764	172	168	659	172	168
R-squared	0.293	0.324	0.423	0.037	0.316	0.422
Weak Instrument				0.085	1.089	21.184
Underidentification				0.556	0.041	0.000

Standard errors in parentheses. Statistical significance ^{a} $p < 0.1$, * $p < 0.05$, ** $p < 0.01$. All specifications include time-, industry-, and location-fixed effects. Standard errors adjusted for clustering at location-skill group level. See text for details on data.

Table B4: Wages and Production across regions and industries by skill-intensity, 2004-2007

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS estimation			IV estimation		
	Inland	Low coast	High coast	Inland	Low coast	High coast
Skill-quartiles based on China NBS data						
Local average wage	-0.055[a]	0.040	-0.183**	5.017	-0.198	-0.454**
	(0.031)	(0.056)	(0.060)	(9.391)	(0.435)	(0.113)
$\times skill_2$	0.069**	-0.045	0.038	0.171	0.321**	0.167[a]
	(0.022)	(0.045)	(0.070)	(0.244)	(0.120)	(0.089)
$\times skill_3$	0.052**	-0.034	0.018	0.135	0.173**	0.118*
	(0.013)	(0.023)	(0.039)	(0.122)	(0.066)	(0.047)
$\times skill_4$	0.038**	0.012	0.009	0.079	0.128**	0.094**
	(0.009)	(0.016)	(0.027)	(0.071)	(0.038)	(0.035)
Value-added	0.650**	0.705**	0.809**	0.631**	0.707**	0.809**
	(0.012)	(0.019)	(0.023)	(0.038)	(0.019)	(0.023)
Local industry wage	0.367**	0.288**	0.386**	0.281	0.294**	0.384**
	(0.019)	(0.025)	(0.032)	(0.176)	(0.030)	(0.032)
Observations	50,729	22,470	38,867	46,815	22,470	38,867
Cluster	771	172	168	662	172	168
R-squared	0.442	0.486	0.507	0.158	0.481	0.505
Weak Instrument				0.077	1.130	20.843
Underidentification				0.574	0.037	0.000
Skill-quartiles based on US NBER Manufacturing data						
Local average wage	-0.037	0.057	-0.232**	4.459	-0.085	-0.563**
	(0.031)	(0.052)	(0.064)	(7.848)	(0.414)	(0.133)
$\times skill_2$	0.150**	-0.089[a]	0.178*	0.131	0.228[a]	0.440**
	(0.024)	(0.049)	(0.074)	(0.156)	(0.128)	(0.100)
$\times skill_3$	0.029**	-0.022	0.018	0.100	0.118[a]	0.157**
	(0.011)	(0.020)	(0.038)	(0.085)	(0.066)	(0.048)
$\times skill_4$	0.010	-0.010	0.035	0.046	0.117**	0.121**
	(0.007)	(0.017)	(0.030)	(0.055)	(0.043)	(0.036)
Value-added	0.649**	0.708**	0.816**	0.633**	0.709**	0.817**
	(0.011)	(0.017)	(0.020)	(0.033)	(0.017)	(0.020)
Local industry wage	0.370**	0.288**	0.387**	0.298*	0.295**	0.387**
	(0.018)	(0.027)	(0.030)	(0.145)	(0.031)	(0.030)
Observations	49,902	22,069	37,666	46,042	22,069	37,666
Cluster	766	172	168	660	172	168
R-squared	0.443	0.484	0.503	0.221	0.480	0.501
Weak Instrument				0.088	1.095	21.017
Underidentification				0.548	0.040	0.000
Skill-quartiles based on Indonesian Manufacturing industry data						
Local average wage	-0.065[a]	-0.018	-0.122*	4.619	-0.214	-0.332**
	(0.033)	(0.063)	(0.059)	(8.317)	(0.437)	(0.115)
$\times skill_2$	0.126**	-0.000	0.034	0.210	0.385**	0.212*
	(0.029)	(0.058)	(0.066)	(0.190)	(0.130)	(0.095)
$\times skill_3$	0.060**	0.010	-0.017	0.133	0.220**	0.014
	(0.013)	(0.027)	(0.032)	(0.113)	(0.065)	(0.042)
$\times skill_4$	0.025**	0.032	-0.051[a]	0.098	0.144**	-0.044
	(0.008)	(0.021)	(0.026)	(0.105)	(0.046)	(0.036)
Value-added	0.650**	0.709**	0.815**	0.632**	0.711**	0.816**
	(0.011)	(0.020)	(0.021)	(0.035)	(0.020)	(0.021)
Local industry wage	0.369**	0.289**	0.389**	0.292[a]	0.291**	0.393**
	(0.018)	(0.026)	(0.032)	(0.157)	(0.029)	(0.032)
Observations	49,842	22,021	37,671	45,985	22,021	37,671
Cluster	764	172	168	659	172	168
R-squared	0.443	0.485	0.504	0.195	0.480	0.503
Weak Instrument				0.085	1.089	21.184
Underidentification				0.556	0.041	0.000

Standard errors in parentheses. Statistical significance ^{a} $p < 0.1$, * $p < 0.05$, ** $p < 0.01$. All specifications include time-, industry-, and location-fixed effects. Standard errors adjusted for clustering at location-skill group level. See text for details on data.

Table B5: Wages and exposure of industries to low-wage competition in Coastal China, 2004-2007

	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline	Single Interactions				Pooled Interactions
Dependent variable: *log Exports*						
Local average wage	-0.232**	-0.181**	-0.210**	-0.200**	-0.292**	-0.207**
	(0.051)	(0.052)	(0.051)	(0.051)	(0.057)	(0.061)
× Asia		-1.496**				
		(0.315)				
× East Asia			-1.417**			-1.190*
			(0.487)			(0.503)
× South Asia				-1.846**		-1.633**
				(0.462)		(0.484)
× Skill-int.					0.469*	0.186
					(0.217)	(0.230)
Value-added	0.182**	0.183**	0.183**	0.183**	0.181**	0.183**
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Local industry wage	0.551**	0.547**	0.549**	0.546**	0.550**	0.546**
	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)
Observations	50,979	50,958	50,958	50,958	50,979	50,958
Cluster	15,732	15,721	15,721	15,721	15,732	15,721
R-squared	0.558	0.559	0.559	0.559	0.558	0.559
Dependent variable: *log Employment*						
Local average wage	-0.147**	-0.125**	-0.131**	-0.136**	-0.152**	-0.128**
	(0.022)	(0.023)	(0.023)	(0.023)	(0.026)	(0.028)
× Asia		-0.567**				
		(0.169)				
× East Asia			-0.785**			-0.740*
			(0.296)			(0.298)
× South Asia				-0.471*		-0.408^{a}
				(0.213)		(0.217)
× Skill-int.					0.036	0.023
					(0.109)	(0.115)
Value-added	-0.027*	-0.021^{a}	-0.021^{a}	-0.021^{a}	-0.027*	-0.021^{a}
	(0.011)	(0.012)	(0.012)	(0.012)	(0.011)	(0.012)
Local industry wage	0.312**	0.308**	0.308**	0.308**	0.312**	0.308**
	(0.018)	(0.019)	(0.019)	(0.019)	(0.018)	(0.019)
Observations	61,342	60,012	60,012	60,012	61,342	60,012
Cluster	18,327	17,844	17,844	17,844	18,327	17,844
R-squared	0.381	0.378	0.378	0.378	0.381	0.378
Dependent variable: *log Production*						
Local average wage	-0.110**	-0.090**	-0.097**	-0.101**	-0.119**	-0.098**
	(0.023)	(0.024)	(0.023)	(0.023)	(0.027)	(0.029)
× Asia		-0.558**				
		(0.165)				
× East Asia			-0.731**			-0.672*
			(0.280)			(0.282)
× South Asia				-0.498*		-0.425*
				(0.212)		(0.217)
× Skill-int.					0.069	0.055
					(0.112)	(0.118)
Value-added	0.771**	0.778**	0.777**	0.777**	0.771**	0.778**
	(0.011)	(0.012)	(0.012)	(0.012)	(0.011)	(0.012)
Local industry wage	0.348**	0.344**	0.344**	0.344**	0.348**	0.344**
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Observations	61,342	60,012	60,012	60,012	61,342	60,012
Cluster	18,327	17,844	17,844	17,844	18,327	17,844
R-squared	0.485	0.484	0.484	0.484	0.485	0.484

Standard errors in parentheses. Statistical significance ^{a} $p < 0.1$, * $p < 0.05$, ** $p < 0.01$. All specifications include time-, industry-, and location-fixed effects. Standard errors adjusted for clustering at location-industry level. East and South Asia, as defined in Figure 1, excludes Thailand, Malaysia, and Mongolia. See text for details on data.

Table B6: Industry attraction in inner China and excess wage growth in coastal high-income locations, 2004-2007

	(1)	(2)	(3)	(4)	(5)	(6)
	All industries		Low-skill (bottom quartile)		High-skill (top quartile)	
	Pooled	by Region	Pooled	by Region	Pooled	by Region
Dependent variable: *log Exports*						
Excess wage coast	0.071	-0.057	0.478*	0.438[a]	-0.006	0.021
(top 50%)	(0.089)	(0.094)	(0.191)	(0.225)	(0.186)	(0.195)
× coast		0.332**		0.525**		-0.075
		(0.104)		(0.193)		(0.212)
Observations	45,441	45,441	12,991	12,991	8,709	8,709
Cluster	379	379	102	102	87	87
R-squared	0.388	0.390	0.439	0.440	0.411	0.411
Dependent variable: *log Employment*						
Excess wage coast	-0.034	-0.081**	-0.042	-0.080	-0.066	-0.078
(top 50%)	(0.025)	(0.028)	(0.062)	(0.065)	(0.056)	(0.066)
× coast		0.079*		0.021		-0.035
		(0.039)		(0.090)		(0.085)
Observations	73,142	73,142	17,721	17,721	14,567	14,567
Cluster	417	417	106	106	102	102
R-squared	0.286	0.288	0.338	0.339	0.301	0.301
Dependent variable: *log Production*						
Excess wage coast	-0.029	-0.073**	-0.030	-0.068	-0.067	-0.085
(top 50%)	(0.024)	(0.027)	(0.066)	(0.074)	(0.059)	(0.070)
× coast		0.075[a]		0.032		-0.023
		(0.039)		(0.088)		(0.087)
Observations	73,142	73,142	17,721	17,721	14,567	14,567
Cluster	417	417	106	106	102	102
R-squared	0.445	0.446	0.422	0.422	0.494	0.494

Standard errors in parentheses; statistical significance: [a] $p < 0.1$, * $p < 0.05$, ** $p < 0.01$. All specifications include year, industry, and location fixed effects, as well as control variables as used in previous specifications. Standard errors adjusted for clustering at CIC industry level.

Table B7: Determinants of a location's attractiveness for exports, employment, and production; Probit estimation, 2004

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All locations	43 coastal and 45 inner Chinese locations					
Attraction of exporting activity							
Coast= 1	0.715**	0.561^a	0.255	0.388	0.304	0.574^a	-0.092
	(0.232)	(0.301)	(0.333)	(0.329)	(0.344)	(0.304)	(0.390)
log Export share			0.550*				0.724*
			(0.241)				(0.283)
log Sectoral Diversity				0.478			0.463
				(0.347)			(0.434)
log Cumulative SEZ Age					0.171		0.023
					(0.188)		(0.213)
log Exposure to low-wage Asia						-0.173	-0.236
						(0.572)	(0.651)
Observations	224	88	88	88	78	88	78
pseudo R-sq.	0.051	0.037	0.094	0.057	0.031	0.038	0.120
Attraction of manufacturing employment							
Coast= 1	0.986**	0.406	-0.293	0.638^a	0.048	0.374	-0.533
	(0.247)	(0.297)	(0.365)	(0.337)	(0.366)	(0.302)	(0.488)
log Export share			1.335**				1.446**
			(0.317)				(0.375)
log Sectoral Diversity				-0.538			-0.998^a
				(0.337)			(0.559)
log Cumulative SEZ Age					0.307		0.494^a
					(0.218)		(0.299)
log Exposure to low-wage Asia						1.054^a	0.886
						(0.639)	(0.812)
Observations	224	88	88	88	78	88	78
pseudo R-sq.	0.100	0.020	0.269	0.046	0.035	0.049	0.372
Attraction of manufacturing production							
Coast= 1	0.787**	0.412	-0.362	0.576	-0.028	0.382	-0.817
	(0.264)	(0.328)	(0.414)	(0.367)	(0.427)	(0.340)	(0.602)
log Export share			1.212**				1.262**
			(0.327)				(0.408)
log Sectoral Diversity				-0.393			-0.371
				(0.365)			(0.633)
log Cumulative SEZ Age					0.469^a		0.568
					(0.271)		(0.379)
log Exposure to low-wage Asia						1.453^a	1.763
						(0.768)	(1.124)
Observations	224	88	88	88	78	88	78
pseudo R-sq.	0.066	0.021	0.251	0.036	0.067	0.073	0.372

Standard errors in parentheses; statistical significance: ^{a} $p < 0.1$, * $p < 0.05$, ** $p < 0.01$. Binary dependent variable equal one, when estimated coefficient for industry attraction in previous specification positive and statistically significant at 10 percent level; else zero. Number of observations corresponds to number of low-income locations, as observed for the year 2004.