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Abstract

The rapid economic development in China has been characterized by levels of income and productivity very heterogeneous across local areas. This work investigates a previously unexplored aspect of such heterogeneity by assessing the degree of within-industry allocative efficiency across provinces in China over the period 1998-2007. Using firm-level data from the surveys conducted by the National Bureau of Statistics on the Chinese manufacturing firms, we measure the degree of resource misallocation by computing the within-industry covariance between size and productivity at the provincial level. The results suggest that within-industry allocative efficiency varies considerably across local areas and that some place-based factors strongly influence resources mobility. Our work sheds some light on the mechanisms at play in the distribution of resources in China and it contributes to the literature investigating the degree of allocative efficiency.
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1. Introduction

In the context of heterogeneous production units, the aggregate productivity depends on both the efficiency of the individual firms and on how inputs are allocated across them. A recent body of empirical studies have tried to ascertain to what extent cross-country differences in aggregate productivity depend on the misallocation of factors of production across firms.[1] In a seminal paper, Hsieh and Klenow (2009) assess the role of misallocation in accounting for cross-sectional gaps in total factor productivity (TFP) between China, India and the United States. They find a large dispersion in factors' wedges and TFP levels across the Chinese enterprises and conclude that in China there must exist large barriers to a productivity-enhancing reallocation of resources. The removal of such hindrances could lead to sizeable collective gains in terms of efficiency and income.

Following Hsieh and Klenow (2009), several papers have investigated the role of factors misallocation in China.[2] Although informative about various aspects of allocative efficiency, these recent works do not tackle the heterogeneous degree of within-industry allocative efficiency across the Chinese provinces and its possible determinants. The rapid economic development in China has been characterized by levels of income and productivity very heterogeneous across local areas. Indeed, regional disparities in China have been widely documented in terms of economic growth (e.g., Fan et al., 2003; Meng et al., 2005), income and consumption inequality (e.g., Du et al., 2005; Bin and Fracasso, 2016; Cheong and Wu, 2013; Kanbur and Zhang, 2005; Westerlund et al., 2010) and productivity level (Rizov and Zhang, 2014), but not in terms of misallocation. This is somehow surprising given that improving within-industry allocative efficiency at the province level is conceivably easier than either modifying the industry composition in each province or reallocating resources across provinces.

Thus, previous works have left a relevant dimension to be explored and this work aims to fill this gap by measuring the degree of heterogeneity in the resource misallocation across provinces. It also contributes to the literature by investigating how local factors correlate with the provincial degree of within-industry allocative efficiency across the firms operating in the manufacturing sectors in China. Among the local determinants of factors' mobility and resource reallocation, the paper considers the role played by agglomeration economies, innovation and knowledge spillovers, quality of human capital, international competition, infrastructures supporting work-related commuting.

The empirical analysis exploits firm-level data from the annual surveys conducted by the National Bureau of Statistics (NBS) on the Chinese firms operating in the manufacturing sectors over the period 1998-2007.[3] In short, the adopted empirical

[1] Among the emerging literature emphasizing the role of misallocation of resources see Banerjee and Duflo (2005); Bartelsman et al. (2009, 2013), among others.

[2] Brandt et al. (2012); Ding et al. (2016), among others.

[3] The NBS firm-level data has been used extensively to study key aspects of industrial dynamics

methodology consists of three main consecutive steps: first, the estimation of firm-level total factor productivity for the Chinese manufacturing enterprises; second, the calculation of the Olley and Pakes (1996)'s decomposition at the industry-province level so as to derive a measure of within-industry allocative efficiency at the provincial level; finally, the estimation of the empirical relationship between within-industry measures of allocative efficiency and a range of place-based factors.

To preview the main findings, the estimation results suggest that within-industry allocative efficiency varies considerably across provinces and over time, confirming a high degree of local heterogeneity also in terms of misallocation. The paper shows that place-based determinants of factors' mobility are associated with the degree of allocative efficiency. These findings shed some light on the mechanisms at play in the distribution of resources in China and inform the authorities on the efficiency-related effects of localised policy measures. This is all the more important in the light of the current emphasis put by the Chinese authorities on supply-side reforms directed to improve the allocation of resources. Understanding how local factors influence within-industry allocative efficiency is important for the political debate on what interventions could both enhance efficiency and reduce regional inequality. This appears particularly important in the light of the recent literature showing that the allocation of resources across heterogeneous firms is a key determinant of the marked productivity differentials across countries (see, among others, Restuccia and Rogerson, 2013; Bartelsman et al., 2013), and in consideration of the key role that productivity gains may play in the preservation of a high-growth trajectory in China (Ding and Knight, 2011).

Our paper relates to the literature on resource allocation in China, relatively recent but already rich. Using aggregate provincial data for all non-agricultural sectors, Brandt et al. (2013) find evidence on the evolution of the within-industry misallocation of total factor productivity across provinces, as well as between state and non-state sectors. Focusing on output and input wedges, they find constant TFP losses due to persistent between-province resource misallocation and to within-province misallocation between state owned enterprises (SOEs) and non-state owned enterprises.. Due to their use of aggregate regional data, Brandt and co-authors cannot assess the extent of within-industry allocative efficiency, notwithstanding their results on the relevance of the differences between SOE and non-SOE would suggest to explore the within-industry dimension. Chen et al. (2011) analyze data aggregated at the industry level over the period 1980-2008 and measure the changes in TFP due to the reallocation of factors of production across industries in the whole country. They find that the contribution to growth of such process of structural change has been substantial, though decreasing after 2001. Also in this work within-industry allocative efficiency is not addressed.

Turning to the published evidence based on microeconomic firm-level data, Hsieh

in China. To obtain reliable information, we clean the data following the steps described in the pioneering work by Brandt et al. (2014).

[3]A large misallocation between SOE and non-SOE has been found also by Song et al. (2011)

and Klenow (2009) are among the first to analyse the static allocation problem in manufacturing sectors in China. Focusing on the difference between the value marginal product and the cost of inputs, they find a large dispersion in factors' wedges and TFP levels across the enterprises operating in China. They conclude that the reduction of within-industry misallocation to the levels observed in the U.S. economy would increase productivity by 30-50 percent in China. Analyzing firm-level productivity growth, Brandt et al. (2012) find that within-industry reallocation of resources between the firms located across the entire country could have a positive impact on aggregate growth. Both Hsieh and Klenow (2009) and Brandt et al. (2012) focus on nationwide measures of misallocation and neglect the geographic dimension of allocative efficiency. Despite an improvement in the efficiency of allocation over time, the reallocation across existing firms has been limited and changes at the extensive margin account for most of TFP growth.

The existence of regional differences in allocative efficiency has instead been addressed by Rizov and Zhang (2014), who examine the differences in average productivity levels for three regional typologies of provinces by performing a shift-share decomposition of firm-level productivity averaged at the industry level for each regional typology. As they find that dense, coastal and highly urbanized regions exhibit the highest average productivity (regardless of the industry composition), the authors conclude that there exist very small differences in allocative efficiency across industries within each regional typology. Two issues are worth noting: first, given their interest on average values of productivity at the industry level, they overlook within-industry allocative efficiency; second, they focus on three typologies of provinces rather than analyzing the variability across all individual provinces. Another recent contribution is that by Ding et al. (2016) who discuss the determinants of China's productivity growth using firm-level data and applying the Haltiwanger approach (Foster et al., 1998) to decompose productivity growth. They conclude that a resource reallocation across industries could conduct to greater improvements in TFP growth than reallocation across provinces. Although based on growth rates rather than levels of productivity, this result suggests that within-industry resource allocation at the provincial level may be the most relevant dimension of allocative efficiency to consider.

This work innovates upon the existing literature along three dimensions. First, it moves the investigation beyond shift-share analyses of differentials in average productivity among dichotomous classes of regions (such as coastal/inland or rural/urban groups, as in Rizov and Zhang, 2014)[4]. Second, it focuses on the degree of within-industry allocative efficiency calculated at the provincial level rather than on a nationwide basis (as done by Hsieh and Klenow, 2009; Brandt et al., 2012; Hashiguchi, 2015; Ding et al., 2016). As the brief overview makes clear, Ding et al. (2016) is the only

[4]Some authors have analysed differentials in productivity levels and growth rates among ownership groups (such as state and private enterprises, as done by Brandt et al., 2012, 2013). Although ownership variables will be considered in the empirical analysis, addressing differential performances across ownership groups falls beyond the scope of this analysis.

study that presents the province-level results of productivity decomposition. Differently from their work, we focus on levels of productivity rather than its growth rates. Moreover, and this is our third contribution, this paper combines provincial measures of within-industry allocative efficiency with other regional data capturing the extent of factors' mobility.

The remainder of the paper continues as follows. Section 2 presents the data and the estimation of the TFP at the firm level. The theoretical underpinnings of the Olley and Pakes (1996)'s decomposition of TFP are presented in Section 3. Section 4 reports the results of the decomposition applied to calculate the degree of within-industry allocative efficiency at the provincial level and as well as its relationship with variables capturing the degree of local factors' mobility. Section 5 closes the work.

2. Data and TFP estimation

The analysis covers microeconomic firm-level data derived from the annual accounting reports filed by Chinese industrial firms. This dataset has already been explored by a number of authors, such as Brandt et al. (2012); Rizov and Zhang (2014); Tian and Yu (2015); Yu (2015); Ding et al. (2016); Manova and Yu (2016). All the SOEs and the non-SOE firms with annual sales of at least five million Yuan are included in the sample. Although firms with annual sales below such threshold are not included, they account for less than 10% of the aggregate output (in 2004) and their exclusion has been shown not to bias the empirical analysis.

The initial (unbalanced) dataset on all the industrial sectors covers more than 2 million firm-year observations, ranging from 165,000 firms in 1998 to almost 337,000 firms in 2007. Table 1 reports the main statistics for the variables at the core of the empirical analysis. For the sake of brevity, we refer to Brandt et al. (2012, 2014) for a detailed description of this dataset and for a discussion of data issues that need to be addressed to obtain reliable information, necessary in particular to ensure a correct matching of the reporting firms over time (whereby restructuring processes and privatizations are duly taken into account). Given the focus on the within-industry allocative efficiency in the manufacturing sectors, all the non-manufacturing firms are dropped from the dataset. Moreover, observations with negative values for one of the key variables (i.e., output, capital, intermediate input, labour, value added) are dropped from the sample. After cleaning the data and taking manufacturing firms only, we end up with an unbalanced panel that increases in size from 121,505 firms in 1998 to 291,076 in 2007.

The analysis on the remaining manufacturing enterprises proceeds with the estimation of the coefficients of a Cobb-Douglas production function for each of the 29 two-digit industries. As pointed out by Van Beveren (2012), estimating firm-level TFP requires to deal with a number of econometric issues: a simultaneity bias (as decisions about inputs may be influenced by the productivity level), a potential omitted variable bias and a sample selection bias (due to firms' entry and exit associated with productivity). Following the literature, we address these issues by estimating a para-

Table 1: Original Sample

Year	# Firms	Output	Sales	Employment
1998	165,118	6.77	6.54	56.4
1999	162,033	7.27	7.06	58.1
2000	162,883	8.57	8.37	53.7
2001	169,028	9.4	9.18	53
2002	181,557	11.1	10.9	55.2
2003	196,222	14.2	13.9	57.5
2004*	279,090		19.9	66.3
2005	271,835	25.2	24.7	69.3
2006	301,961	31.7	31.1	73.5
2007	336,768	40.5	39.8	79.3

Notes: Sales and output in trillion RMB. Employment in million workers.* Industrial output is not available for 2004 (see also Brandt et al. (2014)).

metric production function with the methodology proposed by Olley and Pakes (1996), whereby investment proxies for unobserved productivity.[5,6] Our left hand side variable is (log) value added. Since for 2004 value added is not available, we follow Nie et al. (2012) and estimate the variable according to accounting rules: industrial value-added = total industrial output value − intermediate industrial input + value-added tax.

Using the estimated coefficients of the production function for an industry, we then calculate the level of TFP for each firm in such industry. It is worth recalling that, by construction, this measure of productivity should be best interpreted as a relative measure within the industry to which the firm belongs. This implies that our focus on within-industry allocative efficiency is consistent with the methodology used to calculate firms' TFP levels.[7] To address possible problems with outliers, we drop extreme values by trimming 1% of the observations from the top and bottom percentiles of the estimated TFP, as often done in the literature on allocative efficiency.

Figure 1 reports the distribution of firms' total factor productivity computed using

[5] While other estimation methods are available, Olley and Pakes (1996) is the most popular approach among the empirical works focusing on firm-level data in China. This is possibly due to the dismal results (i.e., negative estimated coefficients) obtained after applying the approach developed by Levinsohn and Petrin (2003) and its recent reformulation by Wooldridge (2009), as found by Ding et al. (2016) and confirmed by our (unreported) results.

[6] As most variables are deflated with industry-level deflators, the estimated measures of TFP are revenue-based.

[7] Although our analysis focuses on resource misallocation within-industry and provinces, we estimate the production function at industry level only. This is because there are not enough companies in all provinces for all sectors. Moreover, there are no reasons to assume that production functions differ across provinces for the same industry.

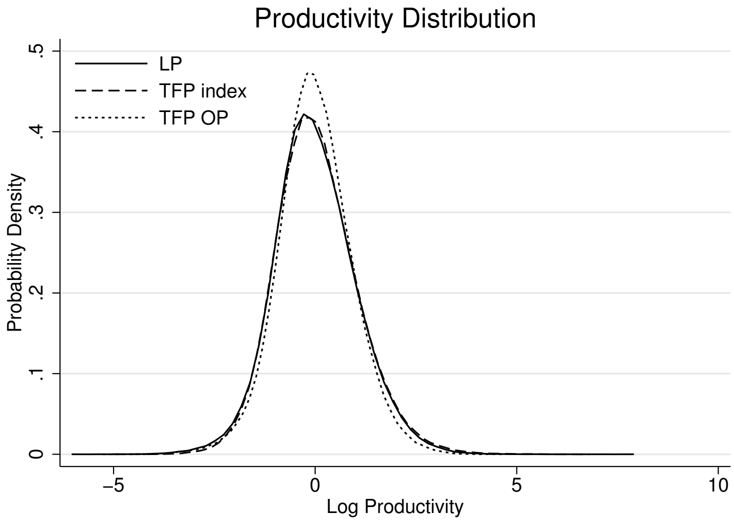

Figure 1: TFP distributions for 2007 using three different methodologies (normalized by sector): labour productivity (LP), TFP index (Caves et al., 1982), and TFP using the Olley and Pakes (1996) approach (TFP OP).

the Olley and Pakes (1996) approach for 2007. To verify robustness, we follow Brandt et al. (2012) and measure total factor productivity using a straightforward index number, which does not require the estimation of any parameters, as suggested by Caves et al. (1982).[8] Also, we report the distribution of (log) labour productivity, computed as the ratio between value added and labour. The figure confirms that the shape of firms' productivity distribution does not change by using different approaches.

3. Within-industry allocative efficiency at the provincial level

The literature has followed different approaches to measure the degree of resources misallocation. Restuccia and Rogerson (2013) provides a comprehensive survey of the key contributions from the existing literature. In particular, the authors distinguish among two main approaches which they refer to as the *direct* and the *indirect* one. While the first approach tries to directly find the factors that generate misallocation and assess the importance of these specific underlying sources in generating inefficiencies, the second methodology focuses on the net effect of the entire bundle of underlying

[8]The multilateral productivity is computed as the difference between a firm's (log) output deviation from the mean in the industry, minus a firm's (log) labour deviation from the mean, weighted by the wage bill in value added (S_{it}), and a firm's (log) capital deviation from the mean, weighted by $1 - S_{it}$.

determinants of factors' misallocation.[9]

Among various alternative ways to measure the degree of within-industry allocative efficiency, this work follows the *indirect* approach proposed by Bartelsman et al. (2013) who focus on the covariance between firm size and productivity.[10] Accordingly, since more productive firms tend to be larger than less productive ones, the within-industry covariance between size and productivity is a robust measure to asses the extent of misallocation.

To compute the covariance measure, Bartelsman et al. (2013) exploit the empirical decomposition of the productivity at the industry level performed in the seminal contribution by Olley and Pakes (1996). The index of productivity for the industry I (Π_I) can be defined as the weighted average of the productivity of the firms operating in the industry. This, in turn, can also be rewritten as the sum of the unweighted average of firm-level productivity and the covariance between firm size and firm productivity. Accordingly, the index of productivity for the industry I can be decomposed as follows

$$\Pi_I = \frac{1}{N_I} \sum_{j \in I} \pi_i + \sum_{j \in I} (s_j - \bar{s}_I)(\pi_j - \bar{\pi}_I) \tag{1}$$

where s_j is the share of activity for the firm j in the industry I, π_j is the firm-level productivity (in logs) of firm j and the bar over a variable represents the unweighted average for industry I. If firms with higher than average productivity also exhibit a share of activity greater than the average share, then the covariance term (and thus the degree of allocative efficiency) is high. It is worth noting that the use of the logarithm of firm-level productivity makes the second term scale invariant and allows to compare the covariance terms across different industries.

As a preliminary exercise we show the aggregate covariance, computed as a weighted average of each sector covariance obtained from equation 1. Visual evidence on the evolution of average allocative efficiency across industries at the national level is offered in Figure 2. The shares to calculate the covariance terms and the weights to aggregate the industries are based either on value added (dark grey bars) or on final sales (light grey bars).

Figure 2 conveys three main messages. First, this measure of allocative efficiency is positive and higher than 0.5, irrespectively of the variable used to weight the observations. This suggests that, despite possible improvements in the allocative efficiency, all in all resources are not too badly allocated across firms within the same industry-pair.[11]

[9]Key contributions among the direct approach are, among others, Banerjee and Duflo (2005) who focus on credit market imperfections; Pavcnik (2002) and Lileeva and Trefler (2010) who look at the role of trade reforms; and Lagos (2006) who analyzes the effect of employment protection legislation. See Restuccia and Rogerson (2013) for a detailed review of the literature.

[10]A second important contribution among the *indirect* approach is the one provided by Hsieh and Klenow (2009). Their main idea is that, in a frictionless world, marginal revenue products should be equalized across firms and any deviation provides evidence of misallocation.

[11]The high value for the covariance measure in 2004 can be due to the fact that value added, used

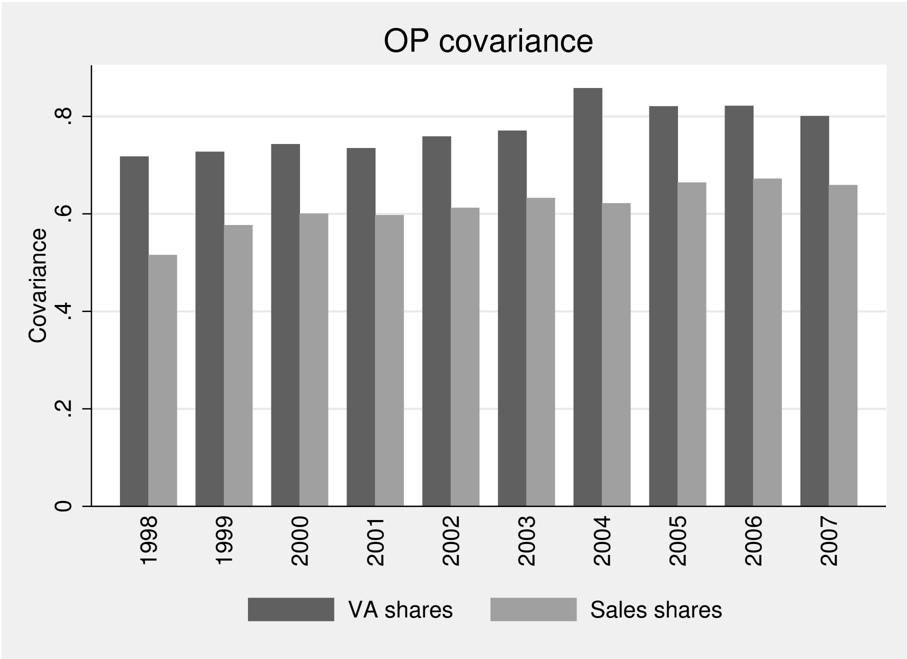

Figure 2: The figure reports aggregate covariance, computed as a weighted average of each sector covariance obtained from equation 1. The shares to calculate the covariance terms and the weights to aggregate the industries are based either on value added (dark grey bars) or on final sales (light grey bars).

Second, there is an upward trend in allocative efficiency (with an overall increase of 10% when measured in value added and of 20% when measured in sales), a result that is in line with what suggested by Figure 6 of Brandt et al. (2013)'s article. Third, allocative efficiency is higher when the share of activity is measured in terms of value added: this suggests that, in accordance with abundant anecdotal evidence, there exist in China several companies with large sales but limited value added and low productivity.

The main aim of our work is to assess the degree of heterogeneity of within-industry allocative efficiency at the provincial level. Consistently with this objective, we do not pool all firms within the same industry at the national level but rather conduct the analysis separately for each industry-province pair. Indeed, due to our focus on the differences in the within-industry resource misallocation across the Chinese provinces, the Olley and Pakes (1996)'s decomposition is subsequently applied to industry-province pairs as indicated in following equation

$$\Pi_{Ip} = \frac{1}{N_{Ip}} \sum_{j \in Ip} \pi_i + \sum_{j \in Ip} (s_j - \bar{s}_{Ip})(\pi_j - \bar{\pi}_{Ip}) \tag{2}$$

to estimate TFP, has been computed for this year, as specified in Section 2.

where s_j is the share of activity for the firm j in industry I and province p, π_j is the firm-level productivity (in logs) of firm j in industry I and province p, and the bar over a variable represents the unweighted average at the level of the industry-province pair Ip.

Repeating the decomposition for each industry-province pair and aggregating the industry-specific covariance terms at the provincial level, one can identify non-negligible differences across regions as well as diverse patterns of change over time. Table 2 reports the weighted average values of the industry-specific covariance terms across provinces in three different years (1998,2003,2007); both the shares to calculate the covariance terms and the weights to aggregate the industries are based on value added.

Table 2 suggests that there is a remarkable degree of heterogeneity for the within-industry allocative efficiency across the Chinese provinces and over time at the provincial level.[12] This source of variation across both time and unit dimensions is crucial for the identification of the empirical relationships between allocative efficiency and regional factors associated with factors' mobility, which this work endeavours to study for the first time and that represents the focus of the next Section.

4. Allocative efficiency and factors' mobility at the provincial level

4.1. Proxies of local factors' mobility

This Section focuses on the analysis of the relationship between the degree of within-industry allocative efficiency at the provincial level and a number of local factors which are potentially associated with the local degree of factors' mobility. Most of the variables considered, in fact, are not to be interpreted as direct determinants of allocative efficiency for they rather stand as proxies of the ultimate determinants of factors' mobility, for which there are no available measures at either the industry or the province level.

The size of the local economic activity and output per capita are often linked to each other due to agglomeration economies, sorting and selection effects, as shown by a very rich literature on agglomeration economies (see, among others, Glaeser et al., 1992; Rosenthal and Strange, 2004; Beaudry and Schiffauerova, 2009; Puga, 2010). What is not clear, however, is whether allocative efficiency is also associated with agglomeration and, if so, what mechanisms are at work. It is possible, for instance, that tougher selection in areas with large economic activity entails that only talented firms survive and that resources are reallocated towards such more productive firms: this

[12]It should be kept in mind that the covariance term captures only the degree of allocative efficiency, and not total efficiency. Accordingly, regions that are often considered as highly (poorly) efficient do score low (high) in terms of covariance. This is neither a problem nor a puzzle. There is no obvious reason why a province where firms are, on average, more productive should also exhibit resources allocated in a more efficient way across firms. Indeed, understanding the determinants of the different degrees of allocative efficiency requires the kind of empirical analysis this work focuses on.

Table 2: Provincial average covariance for manufacturing firms

Province	1998	2003	2007
Anhui	.6563302	.783621	.6387467
Beijing	.9853951	.9421051	1.047713
Chongqing	.4753377	.5513393	.7397631
Fujian	.7720624	.7466992	.8174968
Gansu		.6539792	.4291943
Guangdong	.9371259	.9808052	.9286086
Guangxi	.7563147	.6504186	.5362545
Guizhou	.5999781	.7353761	.6730349
Hainan	1.036434	.8608752	.8612115
Hebei	.4853942	.5839964	.6796451
Heilongjiang	.5638765	.6085675	.6378533
Henan	.457006	.4529512	.5451006
Hubei	.5318852	.4887653	.7659075
Hunan	.8169515	.6244939	.5358993
Inner Mongolia	.4148225	.4191071	.5858169
Jiangsu	.5515385	.6917213	.6992645
Jiangxi	.6222034	.5775977	.427314
Jilin		.9597966	1.061826
Liaoning	.4985662	.5725719	.7008664
Ningxia	.7995397	.4237539	.3091947
Qinghai	.6753541	.3196397	.5797503
Shaanxi	.6782627	.6919494	.5381978
Shandong	.5209405	.7262504	.7265355
Shanghai	.7480816	.8448728	.7924417
Shanxi	.3726293	.5475637	.5001348
Sichuan	.7220221	.5561758	.5818148
Tianjin	1.363282	1.057267	1.38633
Tibet	1.70455	1.059431	.553218
Xinjiang	.7232926	.5359651	.3446379
Yunnan	1.094802	.6674356	.6744579
Zhejiang	.4920945	.5622319	.6342571

Notes: Provincial average covariance for manufacturing firms. VA shares are used as weights to calculate covariance and to aggregate industries. Covariances for Gansu and Jilin are missing in 1998 due to the insufficient number of firms to calculate the statistics.

sorting effect would lead to a positive association between agglomeration and within-industry allocative efficiency. Similarly, higher allocative efficiency in areas with plenty of economic activity may be a consequence of a good match between firms and local resources (Duranton and Puga, 2004). These mechanisms are in line with the idea that where administrative restrictions to the movement of workers are lower in China, the better is the matching between firms and workers.[13]

Plenty of studies have documented a positive correlation between innovation and productivity at the micro level (see Syverson, 2011, for an overview). To the best of our knowledge, however, it is not yet clear what relationship exists between the innovative stance of firms in a region and the local degree of allocative efficiency. Innovation and adoption of new technologies may in fact stimulate a business environment encouraging experimentation and fast reallocation of resources across firms (Collard-Wexler and Loecker, 2015), leading to a positive association. To the extent that innovation works as a proxy for the degree of economic dynamism and factors' reallocation, then, measures of innovation can be employed to test whether the relationship between the latter and the within-industry allocative efficiency is positive.

The literature has established the existence of a positive correlation between the stock of human capital and firm productivity (see again Syverson, 2011). It could be argued, however, that investment in education and training may also promote economic dynamism and thus facilitate a better match between firms and employees. This, in turn, could be reflected into a higher allocative efficiency at the regional level. This matching mechanism complements that mechanism associated with agglomeration externalities (in turn related to the size of the local pool of labour).

The relationship between integration in international trade and productivity has been at the center of much recent research and it depends both on the adjustments occurring within firms due to their engagement in international activities and on the reallocations of resources across firms along the productivity distribution, as suggested by Melitz (2003). In general, one would expect that the higher the degree of internationalization of the productive system, the higher is the allocative efficiency associated with a tougher selection process. As pointed out by various authors, in fact, this may not be the situation in China as Chinese exporters do not seem systematically more productive than non-exporters, as instead occurs in developed economies. According to Yang and He (2014b), this situation could be the by-product of the local export spillovers associated with industrial agglomeration: these spillovers would allow less productive firms to remain in activity. If the spillover channel dominates the selection one, a negative relationship between allocative efficiency and the local average degree of international integration may arise because areas with very many exporters may be inhabited by large and little productive firms.

The degree of within-industry allocative efficiency can also be influenced by other features of the local economy. Different types of prevalent firm ownership, for instance, may reflect the diverse degrees of factors' mobility (Hashiguchi, 2015). An oversized

[13]Notably, there might be complementarities among selection, sorting and agglomeration, as shown by Behrens et al. (2014).

industrial sector at the local level may reflect production overcapacity, that may be interpreted as a sign of limited factors' mobility and resource misallocation, as recently pointed out by the European Chamber of Commerce in a 2016 report titled "Overcapacity in China".[14] Factors' mobility may also depend on the infrastructures supporting work-related commuting (Ghani et al., 2016): higher local endowments of services to facilitate the mobility of the workers are likely to affect positively the degree of allocative efficiency. Finally, if the size of local investment in the protection of the environment proxies for the degree of quality-enhancing dynamism at local level, it could be positively associated with the local degree of allocative efficiency.[15]

To operationalize these intuitions and test their relevance, we adopt a number of measures that help to capture the mechanisms described abroad. Some of these measures are derived from the original firm-level dataset by the National Bureau of Statistics and calculated for each province-industry pair. Other variables are drawn from official Chinese statistical yearbooks (various years 1999-2008) also published by the National Bureau of Statistics: they take different values for each province but without variation across industries.[16] Table A.1 in Appendix A lists all the variables used throughout our empirical analysis and the data sources.

To account for localization and urbanization economies, Combes and Gobillon (2015) and Fracasso and Vittucci Marzetti (2017) suggest to employ two complementary variables: one measuring the size of the local industry (either in absolute terms or as a ratio over the total size of the local economy) and the total size of the local economy. Accordingly, we calculate the specialization index ($\text{Specialization}_{Ip}$), that consists in the ratio of the value of local production of sector I in province p over the total value of the local production in p) and the value of local production in province p (Local activity_p).

To measure the features of the educational systems at the provincial level, we employ the ratio of public expenditures for education over the local GDP (GovExpEdu_p), as well as the relative importance of higher education calculated as the ratio of the number of students in higher education over those in primary education (Student Ratio_p).

To proxy for the extent of innovation at the local level, we adopt the (log) number of patents application per capita examined in the province ($\text{Patents Application}_p$). Firms' international integration is measured in terms of the percentage of exporting firms in industry I and province p ($\text{International Integration}_{Ip}$) and is calculated on the basis of the original dataset of firm-level data discussed above.

[14]Overcapacity can also cause allocative inefficiency to the extent it stymies innovation and firms' dynamism. Overcapacity can help to understand other three phenomena in China for which there is ample empirical evidence: soaring debt-financed investment, large non-performing loans, and rapidly falling domestic and international prices.

[15]We would like to stress that this is not a claim that there is a causal relationship between local investment in the protection of the environment and allocative efficiency.

[16]The dataset contains values for 30 of the 31 Chinese provinces and municipalities. Tibet is removed because of missing data.

As to the structure of the economy, we include the percentage of foreign-owned enterprises in industry I and province p (ShareFOR$_{Ip}$), again derived from the original dataset of firm-level data, and the share of employees in the industrial sectors of the local economy (2^{nd}Sector$_p$) (that, we recall, is meant to proxy for overcapacity). The number of public buses per 10,000 persons (Bus$_p$) in province p is used as a proxy of the local transport services. The ratio of investment in anti-pollution schemes over GDP at the provincial level (Investment in Antipollution$_p$) captures the extent of quality-enhancing economic dynamism at the local level.

4.2. Empirical results

To study the relationship between the degree of within-industry allocative efficiency at the provincial level and the above mentioned factors potentially associated with factors' mobility, we estimate the following functional form

$$Cov_{Ipt} = \alpha + \beta_1' \mathbf{X_{pt}} + \beta_2' \mathbf{Z_{Ipt}} + d_t + d_I + d_p + \epsilon_{Ipt} \tag{3}$$

where Cov_{Ipt} is the covariance term calculated for industry I and province p for the year t via the Olley and Pakes (1996)'s decomposition, X_{pt} is a set of time-varying province-specific factors and Z_{Ipt} is a set of variables varying across industries, provinces and time. The estimation includes time, industry and province fixed effects to control for possible time-invariant omitted factors.

To start, we consider the variables related to economic agglomeration, investment in education, innovation and international integration. The results are reported in the first five columns of Table 3. With the exception of $GovExpEdu_p$, all variables are statistically significant. The results indicate that allocative efficiency is higher where the level of agglomeration is higher, where higher education is relatively more developed, where innovation is more intense and where firms' participation in international trade is less widespread.

In the columns from 6 to 8 of Table 3, we add the remaining above mentioned factors that may be associated with different degrees of allocative efficiency, i.e. share of foreign firms, the share of employees in the industrial sectors of the local economy, and the number of public buses per 10,000 persons. The share of foreign firms in the industry-province is positive and significant, thereby suggesting either that foreign firms contribute to the mobilization of local resources (causal interpretation) or that they choose to operate in industries and areas where mobility is higher (signalling interpretation). The relative size of the industrial sector, the endowment of bus transport services and investment in antipollution schemes do not appear to be significant. Although the significance of the education variable is reduced after the inclusion of these additional variables, the adjusted R-squared marginally increases moving from the first to the last column.

The low significance of the variables varying only across provinces can in part be due to the inclusion of province fixed effects in the estimations, whereby the main source of identification is the variation of the measures over time. To exploit cross-province differences while controlling for structural differences between macro-regions in China, we then drop province fixed effects and include four variables to differentiate the macro-regions. The first variable is a time-invariant dummy for the Special Economic Zones (SEZ_{pt}), established before the beginning of the sample at hand; a second variable takes value 1 for the Western provinces after the year 2001, when the national authorities delivered a plan to foster the development of these inner areas, known as the strategy "Western Development" (Go West_{pt}); the third variable takes value 1 for the provinces in the North-East region after the year 2003, when the government launched a regional project targeting at the revitalization of the traditional North-East industry (Go N-East_{pt}); finally, a forth dummy variables takes value 1 for the Central provinces after the year 2004, following another regional project aiming to promote the rise of central China (Go-Central_{pt}).

The estimates are reported in Table 4. Collectively interpreted, the estimated coefficients of the newly introduced dummy variables suggest that the coastal areas (i.e., the Special Economic Zones) have a higher degree of within-industry allocative efficiency and that the policy plans to promote economic development in various regions did not improve within-industry allocative efficiency.[17] This is in line with anecdotal evidence suggesting that such large interventions by the authorities have often focused on massive investment plans worsening capital (as well as land and energy) misallocation. This interpretation is also supported by the negative and significant coefficient for the variable proxying for overcapacity in the industrial sector, which was insignificant when provincial fixed effects capture the variation across provinces.

5. Closing remarks

Although rich, the literature on allocative efficiency in China has neglected the heterogeneous degree of within-industry allocative efficiency across the Chinese provinces, even though improving this dimension of allocative efficiency is conceivably easier than modifying the industrial composition of the provincial economy (i.e., structural change) and than reallocating resources across provinces within an industry.

By calculating the degree of within-industry allocative efficiency as the covariance between firm size and productivity (as pointed out by Olley and Pakes, 1996) in each industry-province pair in China, this work has filled this gap in the literature and provided evidence of a large variability of within-industry allocative efficiency across provinces and over time.

Moreover, this work gauges the relationship between local factors' mobility and the degree of within-industry allocative efficiency at the provincial level by estimating the empirical relation of this latter with a number of local features of the economy associated with different degrees of factors' mobility. The analysis reveals that agglomeration is positively associated with higher allocative efficiency, possibly because the former

[17] This, it should be noted, does not prevent these policy measures from having improved other dimensions of allocative efficiency.

is characterised by higher mobility and a better match between workers and firms. Similarly, greater local efforts to support higher education go together with higher degrees of allocative efficiency, possibly because better educated workers are more mobile and employable. Provinces characterized by high overcapacity and lower innovation, in turn, are also signed by lower within-industry allocative efficiency. Somehow surprisingly, the stronger the engagement of local firms in international trade the lower allocative efficiency: this may be the result of export spillovers than prevent selection mechanisms to operate, as suggested by Yang and He (2014a).

Although this work focuses on within-industry allocative efficiency, there is no presumption that this dimension of the overall level of static efficiency is the most relevant one. Accordingly, the reader should consider this work as complementary to the analyses that either consider within-industry allocative efficiency at the national level or to those focusing on inter-industry reallocation at the provincial level.

Table 3: Within-industry allocative efficiency and regional proxies of factors' mobility

Dep. Var.	Cov_{Ipt}							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Specialization$_{Ipt}$	1.028***	1.028***	1.029***	1.026***	1.069***	1.025***	1.025***	1.011***
	(0.198)	(0.198)	(0.199)	(0.197)	(0.193)	(0.182)	(0.182)	(0.187)
Local activity$_{pt}$	0.158*	0.157*	0.160*	0.152*	0.140*	0.174**	0.173**	0.167**
	(0.084)	(0.084)	(0.080)	(0.079)	(0.079)	(0.073)	(0.072)	(0.072)
GovExpEdu$_{pt}$ (% GDP)		0.034						
		(0.031)						
Student ratio$_{pt}$			0.218***	0.165***	0.166***	0.111*	0.111*	0.087
			(0.064)	(0.051)	(0.051)	(0.064)	(0.064)	(0.061)
Patents application$_{pt}$				0.088**	0.086**	0.099**	0.099**	0.111**
				(0.039)	(0.039)	(0.040)	(0.040)	(0.042)
International Integration$_{Ipt}$					-0.152**	-0.191***	-0.191***	-0.191***
					(0.055)	(0.049)	(0.049)	(0.049)
Share FOR firms$_{Ipt}$						0.409**	0.409**	0.395**
						(0.154)	(0.154)	(0.153)
2^{nd} Sector$_{pt}$						-0.005	-0.005	-0.005
						(0.004)	(0.004)	(0.004)
Bus$_{pt}$							0.000	-0.000
							(0.001)	(0.001)
Investment in Antipollution$_{pt}$								-5.035
								(4.790)
N	8,618	8,618	8,618	8,618	8,618	8,618	8,618	8,534
adj. R^2	0.198	0.198	0.200	0.203	0.205	0.210	0.210	0.213

Notes: Standard errors clustered at province level in parentheses. Year, Sector and Province fixed effects.
* p<0.10, ** p<0.05, *** p<0.01.

Table 4: Within-industry allocative efficiency and regional proxies of factors' mobility

Dep. Var.	Cov_{Ipt}	
	(1)	(2)
$\text{Specialization}_{Ipt}$	1.080***	1.039***
	(0.194)	(0.183)
Location_{pt}	0.023*	0.026**
	(0.012)	(0.013)
$\text{Student ratio}_{pt}$	0.167***	0.101*
	(0.059)	(0.057)
$\text{Patents application}_{pt}$	-0.008	0.015
	(0.020)	(0.019)
$\text{International Integration}_{Ipt}$	-0.146**	-0.176***
	(0.059)	(0.049)
$\text{Share of FOR}_{Ipt}$		0.413***
		(0.136)
2^{nd}Sector_{pt}		-0.005***
		(0.002)
Go N-East_{pt}	-0.052	-0.090***
	(0.033)	(0.026)
Go Central_{pt}	-0.065**	-0.060**
	(0.028)	(0.025)
Go West_{pt}	-0.068**	-0.085***
	(0.027)	(0.023)
SEZ_{pt}	0.115***	0.083***
	(0.027)	(0.025)
N	8,618	8,618
adj. R^2	0.190	0.197

Notes: Standard errors clustered at province level in parentheses. Year and Sector fixed effects.* p<0.10, ** p<0.05, *** p<0.01.

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Appendix A. Data

Table A.1: Variables proxing alternative measures of factors' mobility

Concept	Variable	Description	Data source
Agglomeration	Specialization$_{Ip}$	Ratio of production value of industry I in province p over the total production in province p	Annual firms surveys by NBS
	Local activity$_p$	Value of local production in province p (i.e. total size of local economy)	Annual firms surveys by NBS
Education	GovExpEdu$_p$	Ratio of public expenditures for education over the local GDP in province p	China Statistical Yearbook
	Student Ratio$_p$	Ratio of students in higher education over those in primary education in province p	China Statistical Yearbook
Innovation	Patent applications$_p$	Number (in log) of patents application per capita in province p	China Statistical Yearbook
International integration	International integration$_{Ip}$	Percentage of exporting rms in industry I and province p	Annual firms surveys by NBS
Economic structure	ShareFOR$_{Ip}$	Percentage of foreign-owned enterprises in industry I and province p	Annual firms surveys by NBS
	2^{nd} Sector$_p$	Percentage of employees in the industrial sectors of province p	China Statistical Yearbook
Local transport services	Bus$_p$	Number of public buses per 10,000 persons in province p	China Statistical Yearbook
Environment	Investment in Antipollution$_p$	Ratio of investment in anti-pollution schemes over GDP in province p	China Statistical Yearbook
Macroregional Dummies	SEZ$_p$	Value 1 for Special Economic Zones	
	Go N-East$_p$	Value 1 for North-Eastern provinces after 2003	
	Go Central$_p$	Value 1 for Central provinces after 2004	
	Go West$_p$	Value 1 for Western provinces after 2001	