Regional disparities and productivity in China:

Evidence from manufacturing micro data

Marian Rizov, Xufei Zhang

Department of Economics and International Development, Middlesex University Business School, The Burroughs, London NW4 4BT (e-mail: m.rizov@mdx.ac.uk; x.zhang@mdx.ac.uk)

Abstract. In this paper we first estimate firm-specific total factor productivities within 2-digit manufacturing industries using a semi-parametric algorithm and micro data for the period 2000–2007. Next, to characterize regional disparities in China we compute aggregate productivity by the categories of three regional typologies, based on population density, coastal-inland, and rural-urban criteria. We analyse the productivity differentials across the categories of the typologies by decomposing regional productivity level and growth into productivity effect and industry composition effect. We find clear evidence of regional convergence. Besides density of economic activity, recent policy and structural factors seem to affect regional productivity level and growth differentials.

JEL classification: D24, O49, R11, R30
Key words: Productivity, regional disparities, inequality, convergence, China, micro data

1 Introduction

Regional disparities in China have been widely studied in recent years, both in terms of economic growth (e.g., McMillan et al. 1989; Lin 1992; Rozelle et al. 1998; Fan et al. 2003; Meng and Wang, 2005) and income inequality (e.g., Chen and Ravallion 1996, 2007; Khan and Riskin 2001; Kanbur and Zhang 2005; Du et al. 2005). Many authors argue that historic events (the communist rule and the following cultural revolution in the 50s and 60s, the reform of agriculture in the 70s and 80s, and the "open door policy" promoting trade and industrialization in the 80s and 90s) gradually leading to decentralization and marketization of the Chinese economy have predetermined the inland-coastal (Hao and Wei 2010) and rural-urban (Park 2008) inequality. However, in the inequality debate less attention is paid to regional disparities in terms of productivity.[1] Even though references to implications of income inequality for disparities in productivity have often been made there is lack of studies which directly analyze regional productivity with micro data. An inference that high income inequality across regions maps into similarly high productivity gaps can be misleading.[2]

In a neoclassical model relative factor productivities are exactly equal to relative factor prices across regions and the spatial variation in factor prices is determined entirely from the production side of the economy (e.g., Rice et al. 2006). The model implies perfect mobility of production factors across regions and that factors are paid the value of their marginal product. However, in China factor markets, especially the labor market, are not perfectly competitive and the labor is not perfectly mobile.[3] Then the implication of the model is that lower wages in sparsely populated rural (or inland) areas cannot necessarily be seen as evidence of lower productivity. For workers, lower wages may be compensated by lower commuting and housing costs. Furthermore, lower wages (and land rents) in rural (inland) areas may attract productive firms to relocate from elsewhere unless there were some significant productivity disadvantages (Roback 1982; Combes et al. 2010; Puga 2010).

In recent years, since the beginning of the century, the Chinese government has made a significant policy effort aiming at "building a new socialist countryside" as stated in the 11th Five-Year Plan (Park 2008) and attracting firms inland and into rural areas by, for example,

[1] Recently, Tian and Yu (2012), based on a meta-analysis of 150 primary productivity studies, conclude that regional disparities in TFP growth are still significant as the TFP growth in east China is higher than that in central and west China. However, majority of the studies included in the meta-analysis do not have regional focus, use aggregate (macro) data, are conducted at industry or national level, and use conventional growth accounting or efficiency frontier approaches. Furthermore, China is a huge country with pronounced regional heterogeneity, however, existing studies on regional disparities, at best, consider a crude three categories regional classification (east, central and west provinces).

[2] Indeed, a few recent studies with regional focus find evidence of regional productivity convergence. For example, Deng and Jefferson (2011) using aggregate firm and industry data calculate labor productivity to analyze regional disparities and find strong evidence of convergence in growth rates between inland and coastal regions over the period 1995-2004. Zhang et al. (2011) find similar regional differences and evidence of convergence analyzing the impact of R&D investment and technological progress using unique province level data over the period 2000-2007.

[3] There are high costs of moving such as search costs or disutility of leaving one's home. Furthermore, policies such as the China's Hukou system (e.g., Au and Henderson 2006a; Fan 2008) create barriers to labor mobility.

investing in an ambitious expressway network (Roberts et al. 2012). Therefore, it is possible that the extent of regional income inequalities does not fully reflect regional productivity gaps considering the convergence policies in recent years. Given the lack of appropriate productivity studies for China and because theoretical models linking incomes and productivity cannot provide unambiguous answer on the extent of regional productivity gaps we need reliable empirical evidence on this important issue.[4] Therefore, our main goal in the paper is to generate unbiased productivity measures and document the productivity gaps between the categories of multiple regional typologies, capturing different dimensions of the regional heterogeneity in China.

We estimate total factor productivity (TFP) using micro data, for a large and representative sample of Chinese manufacturing firms over the period 2000-2007. We contribute to the literature by applying an advanced TFP estimation technique following modeling ideas in Olley and Pakes (1996) and Ackerberg et al. (2007). We explicitly model unobserved productivity utilizing appropriately disaggregated (at 6-digit regional level) spatial information and incorporate directly the effects of the location characteristics into the structural estimation algorithm.[5] We then use the estimated firm-specific productivity measures to investigate disparities between the categories of three regional typologies, based on population density, coastal-inland, and rural-urban criteria respectively. Our results add robust empirical evidence to the literature on regional disparities in China. Furthermore, we analyze the productivity differentials across the categories of the typologies by decomposing regional productivity level and growth into productivity effect and industry composition effect. Our analysis indicates that besides density of economic activity (capturing

[4] There are a few recent studies estimating productivity with micro data (e.g., Brandt et al. 2012; Hsieh and Klenow 2009) but they do not explicitly focus on the regional productivity disparities in China.

[5] Previous studies attempting to link location and productivity apply a two-stage analysis. In the first stage authors estimate firm productivity, and in a second stage they proceed to link productivity to regional characteristics. In our view testing for a relationship between location and (unobserved) productivity, *ex post*, is admitting that there is omitted information that should have been used in first place, while estimating the production function.

agglomeration effects), recent policy and structural (historic) factors importantly affect regional productivity level and growth differentials. We find evidence of inland regions and less urbanized, rural areas catching up with the coastal regions and highly urbanized areas in terms of productivity over the period of analysis.

2 A model of productivity and estimation algorithm

Our estimation algorithm is based on a framework, which theoretically derives a productivity measure building on models of industry dynamics by Ericson and Pakes (1995) and Hopenhayn (1992) and modeling ideas in Olley and Pakes (1996) and Ackerberg et al. (2007). The algorithm explicitly incorporates the link between spatial density of economic activity, capturing various agglomeration effects, and productivity as formalized by Ciccone and Hall (1996). The theoretical framework underlying our estimation algorithm, similar to the Olley and Pakes (1996) algorithm is presented in more detail in Appendix 1 and it helps us motivate timing and relational assumptions for the firm decisions.

As in Olley and Pakes (1996) we specify a log-linear (Cobb-Douglas) production function,

$$y_{jt} = \beta_0 + \beta_k k_{jt} + \beta_a a_{jt} + \beta_l l_{jt} + \omega_{jt} + \eta_{jt} , \qquad (1)$$

where the log of value added of firm *j* at time *t*, y_{jt} is modeled as a function of the logs of the firm's state variables at *t*, capital k_{jt} and age a_{jt}, and a variable input, labor l_{jt}. The error structure comprises a stochastic component η_{jt}, with zero expected mean, and a component that represents unobserved productivity ω_{jt}. Both ω_{jt} and η_{jt} are unobserved, but ω_{jt} is a state variable, and thus affects firm's equilibrium choices – the investment demand and the decision to exit, while η_{jt} has zero expected mean given current information, and hence does not affect decisions.

Because productivity ω_{jt} is not observed directly in the data, estimating Equation (1) is affected by simultaneity and selection biases. Simultaneity means that estimates for variable inputs such as labor will be upward biased if an OLS estimator is used, assuming a positive correlation with unobserved productivity. Selection (exit) depends on productivity as well as on the capital stock representing (quasi) fixed cost. Thus, the coefficient on capital is likely to be underestimated by OLS as higher capital stocks induce firms to survive at low productivity levels (Olley and Pakes 1996). Besides these two biases, a potential problem afflicting productivity measure is associated with the spatial dependency of observations within a geo-space. Spatial dependency leads to the spatial autocorrelation problem in statistics since - like temporal autocorrelation - this violates the standard statistical assumption of independence among observations (Anselin and Kelejian 1997).

To deal with the biases, we utilize a (structural) model of unobserved productivity based on the theoretical framework outlined in Appendix 1. The productivity (inverse investment) function $\omega_{jt} = h_t\,(i_{jt}, k_{jt}, a_{jt}, r_t)$ is determined by a firm's capital k_{jt}, age a_{jt}, investment i_{jt}, and the economic environment (r_t) that the firm faces at a particular point in time. The economic environment control r_t, captures characteristics of the input markets, characteristics of the output market, industry characteristics such as the distribution of the (states of) firms operating in the industry. Note that Olley-Pakes formulation allows all these factors to change over time, although they are assumed constant across firms in a given period. Further, it is assumed that productivity ω_{jt} follows an exogenous first-order Markov process $p(\omega_{jt} \mid \omega_{jt-1})$ determined by the information set at time t-1 including past productivity, which is the only unobservable – the Olley-Pakes scalar unobservable assumption.

In this paper we extend the Olley-Pakes model of (unobserved) productivity in two ways. First, we extend the information content of the economic environment control with spatial information, which varies by disaggregated (at 6-digit regional level) spatial units and denote this by r_{jt} where a subscript index j is added. The location-specific information such as population density captures the (agglomeration) effects of density of economic activity on firm productivity and market conditions derived in Ciccone and Hall (1996)[6]; it also allows for some of the competitive richness of the Ericson and Pakes' (1995) dynamic oligopoly model. Furthermore, since we deflate value added with an industry-wide PPI, we do not control for the fact that output and factor prices might be different across firms and/or evolve differently over time. Therefore we have dropped the assumption of industry homogeneity and incorporated the location-specific information in the investment and survival equilibrium equations, derived in Appendix 1. More formally, we explicitly allow demand conditions, market structure and factor prices affecting firm decisions on investment and exit to vary by narrowly defined spatial units (at 6-digit regional level) in China.[7]

Second, we relax the scalar unobservable assumption all together following modeling ideas in Ackerberg et al. (2007) and an application to firm productivity and trade orientation by Rizov and Walsh (2009). We adjust the model of productivity to allow for exporting status, e_{jt}, to be an additional (endogenous) control variable in the firm state space that is driven by lagged productivity as in Melitz (2003). This formulation leads to modeling productivity as a controlled second-order Markov process $p(\omega_{jt} \mid \omega_{jt-1}, \omega_{jt-2})$ where firms operate through time forming expectations of future ω's on the basis of information from two preceding periods. The productivity function then becomes:

[6] Ciccone and Hall (1996) show how density affects productivity in several ways. If technologies have constant returns themselves, but the transportation of products from one stage of production to the next involves costs that rise with distance, then the technology for the production of all goods within a particular geographical area will have increasing returns - the ratio of output to input will rise with density. If there are externalities associated with the physical proximity of production, then density will contribute to productivity for this reason as well. A third source of density effects is the higher degree of beneficial specialization possible in areas of dense activity. We also note that explicitly introducing regional information in the model of the unobservable effectively leads to introducing the advantages of multilevel modeling in our estimation algorithm (e.g., Van Oort et al. 2012).

[7] Note that introducing richer location-specific market structure in the productivity function does minimize the deviation from the original Olley-Pakes scalar unobservable assumption, necessary to invert the investment function, and it may help with the precision of the estimates.

$$\omega_{jt} = h_t\,(i_{jt}, e_{ji}, r_{jt}, k_{jt}, a_{jt})\,. \tag{2}$$

Selection to exporting can reveal better productivity due to higher quality products, know-how, and distribution networks that represent sunk cost to access foreign markets. We specify the propensity to export as a non-parametric function of $i_{jt-1}, k_{jt-1}, a_{jt-1}, r_{jt-1}$ and a vector of other firm-specific characteristics such as type of ownership and sector groupings. In equation (2), we use the propensity to export $\hat{e}_{ji}$, estimated from a Probit model rather than the observed e_{ji} because we treat the exporting decision as endogenous controls. In addition, a set of province (2-digit regional code) dummy variables and a time trend are included in all specifications to control for spatial clustering and policy specificities at province level, and by time period (Rizov and Walsh 2011).[8]

Substituting equation (2) into the production function (1) gives us:

$$y_{jt} = \beta_0 + \beta_k k_{jt} + \beta_a a_{jt} + \beta_l l_{jt} + h_t(i_{jt}, r_{jt}, e_{jt}, k_{jt}, a_{jt}) + \eta_{jt}\,. \tag{3}$$

In Equation (3) as in Olley and Pakes (1996) the productivity function *h*(.) is treated non-parametrically using a polynomial (here and everywhere in the following steps we use 3rd-degree polynomial). The non-parametric treatment, however, results in collinearity and requires the constant, k_{jt} and a_{jt} terms to be combined into a function $\phi_t(i_{jt}, r_{jt}, e_{jt}, k_{jt}, a_{jt})$ such that Equation (3) becomes:

$$y_{jt} = \beta_l l_{jt} + \phi_t(i_{jt}, r_{jt}, k_{jt}, a_{jt}, e_{jt}) + \eta_{jt}\,. \tag{4}$$

Equation (4) represents the first stage of our estimation algorithm and we estimate it using OLS.

[8] Note that regional dummy variables will also control to some extend for proximity of firms to economic mass (Rice et al. 2006).

In the first stage of the estimation algorithm we identify only the labor coefficient while capital and age coefficients are identified in the second stage of the algorithm.[9] In the first stage we are also able to estimate $\hat{\phi}_t$ for use in the second stage where we express ω_{jt} as

$$\hat{\omega}_{jt} = \hat{\phi}_{jt} - \beta_0 - \beta_k k_{jt} - \beta_a a_{jt}. \quad (5)$$

Note that the first stage is not affected by endogenous selection because ϕ_t fully controls for the unobservable; by construction, η_{jt} represents unobservable factors that are not known by the firm when investment and exit decisions are made. In contrast, the second stage of the estimation algorithm is affected by endogenous selection because the exit decision in period t depends directly on ω_{jt}.

To clarify the timing of production decisions we decompose ω_{jt} into its conditional expectation given the information about productivity known by the firm in two prior periods (t-2 and t-1) and a residual $\omega_{jt} = E[\omega_{jt} \mid \omega_{jt-2}, \omega_{jt-1}] + \xi_{jt} = g(\omega_{jt-2}, \omega_{jt-1}) + \xi_{jt}$. By construction ξ_{jt} is uncorrelated with information in t-2 and t-1 and thus with k_{jt} and a_{jt} which are determined prior to time t. The specification of the g(.) function is based on the assertion that productivity follows a second-order Markov process. Note that the firm's exit decision in period t depends directly on ω_{jt} and thus the exit decision will be correlated with ξ_{jt}. This correlation relies on the assumption that firms exit the market quickly, in the same period when the decision is made. If exit was decided in the period before actual exit occurred, then even though there is attrition *per se*, exit would be uncorrelated with ξ_{jt} and there will be no selection bias. To account for endogenous selection on productivity we extend the g(.) function with survival propensity as in Olley and Pakes (1996):

$$\omega_{jt} = g'(\omega_{jt-2}, \omega_{jt-1}, \hat{P}_{jt}) + \xi_{jt}, \quad (6)$$

[9] As in the original Olley and Pakes (1996) paper we treat labor as a variable and non-dynamic factor based on the assumption of relative abundance of labor in China and the existing evidence that in Chinese firms it is relatively easy to fire and hire workers.

where $\hat{P}_{jt}$ is the survival propensity score which controls for the impact of selection on the expectation of ω_{jt}, i.e., firms with lower survival propensity which do survive to time *t* likely have higher ω_{jt}'s than those with higher survival propensity. We estimate $\hat{P}_{jt}$ non-parametrically using Probit model with a polynomial approximation. Note that we extend the state variable set with information on location and trade status which are important determinants of the firm exit decision (Rizov and Walsh 2011).

The capital and age coefficients are identified in the second stage of our estimation algorithm. We substitute equations (6) and (5) into equation (1) which gives us:

$$y_{jt} - \hat{\beta}_l l_{jt} = \beta_k k_{jt} + \beta_a a_{jt} + g'(\hat{\phi}_{jt-1} - \beta_k k_{jt-1} - \beta_a a_{jt-1}, \hat{\phi}_{jt-2} - \beta_k k_{jt-2} - \beta_a a_{jt-2}, \hat{P}_{jt}) + \varepsilon_{jt}, \qquad (7)$$

where the two β_0 terms have been encompassed into the non-parametric function, *g'*(.) and ε_{jt} is a composite error term comprised of η_{jt} and ξ_{jt}. The lagged $\hat{\phi}_{jt-1}$ and $\hat{\phi}_{jt-2}$ variables are obtained from the first stage estimates at *t*-1 and *t*-2 periods. Because the conditional expectation of ω_{jt} given information in *t*-2 and *t*-1 periods depends on ω_{jt-2} and ω_{jt-1}, we need to use estimates of $\hat{\phi}$ from two prior periods. Equation (7) is estimated by a non-linear least squares (NLLS) search routine approximating *g'*(.) with a polynomial.[10]

In the empirical analysis that follows we use the production function coefficients $\hat{\beta}_k$ and $\hat{\beta}_l$ consistently estimated from the specification with second-order Markov process and back out unbiased firm-specific productivity (TFP) measures, calculated as residuals from the production function:[11]

$$q_{jt} = \omega_{jt} + \beta_a a_{jt} + \eta_{jt} = y_{jt} - \hat{\beta}_k k_{jt} - \hat{\beta}_l l_{jt}. \qquad (8)$$

[10] Woodridge (2009) presents a concise, one-step formulation of the original Olley and Pakes (1996) algorithm using GMM estimator which is more efficient but less flexible than the standard Olley-Pakes methodology.

[11] As explained in Ackerberg et al. (2007), including age in the specification helps control for cohort effects on firm productivity which improves precision of coefficient estimates; we do not net out the age contribution from the TFP measure.

3 Data and variables

We use the algorithm presented in Section 2 to estimate production functions within 2-digit manufacturing industries for the period 2000-2007. The Annual Surveys of Industrial Production provided by the Chinese National Bureau of Statistics (NBS) is the source of our firm data. It covers all non-state firms with an annual turnover of over five million RMB and all state-owned firms in the manufacturing sector. Thus the data used in the analysis cover the population of medium and large firms, which account for 90% of total manufacturing output of China. Over the period of analysis data comprise, on average, 190000 firms per year. Data include profit-loss account and balance sheet information, firm ownership status, exporting status, and geographic location at county (6-digit regional code) level. Additional data on regional characteristics and density of economic activity are collected from variety of official Chinese statistical sources.

To comprehensively characterize regional disparities in China we use three different regional typologies. The first is based on *density of population* and directly captures the main features of the theory on the link between productivity and density of economic activity (Ciccone and Hall 1996) which underlines our empirical model of unobserved productivity. We adopt the terminology and follow the approach of the OECD (2010) and Eurostat (2010) rural-urban typologies. We classify areas at disaggregated (6-digit regional code) level as *less sparse* when population density is more than 300 inhabitants per km^2, for the inland provinces; for the coastal provinces the threshold is 500 inhabitants per km^2, which is adopted by OECD for the densely populated countries such as Japan and South Korea. The areas with population density below the thresholds are classified as *sparse*.[12]

[12] In 2000 NBS adopted a standard for classifying areas in China primarily on the basis of population density (Park 2008).

The second typology separates the *coastal* and *inland* regions according to the official Chinese classification, based on large, province units. The provinces classified as coastal are Beijing, Liaoning, Tianjin, Hebei, Shandong, Jiangsu, Shanghai, Zhejiang, Fujian, Guangdong, Guangxi, and Hainan, and the rest are classified as inland. This typology is the most straightforward in terms of definition and in the same time it is the most widely used in describing regional disparities in China as numerous studies demonstrate. However, the typology fails to capture the important intra-province regional heterogeneity.

The third, *rural-urban* typology is more complex and builds on the principles of the OECD and Eurostat typologies. It is a combination of a *classification* based on settlement morphology according to the shares of the urban (city) and rural (township - xiang) population as classified by the Chinese NBS and a *definition* based on the density of the population at disaggregate (6-digit regional code) level. In principle, it is possible to have six types of locations – urban (less sparse); urban (sparse); mixed (less sparse); mixed (sparse); rural (less sparse); rural (sparse) similar, for example, to the rural-urban typology in the UK (DEFRA, 2005), but in the case of China this grouping cannot be readily undertaken for analytical purposes as we do not have access to well established morphology of settlements. Therefore similar to the OECD and Eurostat typologies we create three categories. They are defined as: a) highly urbanized areas with high population density (the less sparse category defined in our density of population typology) and proportion of urban population more than 80%; b) urbanized (mixed) areas with low population density (the sparse category) and proportion of urban population between 20% and 80% or proportion of rural population below 50%; c) rural areas with low population density (the sparse category), proportion of urban population below 20% and proportion of rural population above 50%.

Next, we describe our regression variables.[13] The manufacturing industries are identified on the bases of the current Chinese industry classification at the 2-digit level and range between 13 and 43. Thus, in total we separately estimate 30 industries, each containing a sufficient number of firms to apply our estimation algorithm; Appendix 2, Table A1 lists all estimated industries. Ownership status is determined according to the structure of ownership of capital. We follow the Chinese legal definition of ownership and identify firms with 25% or more of their capital owned by foreigners as foreign firms, firms with 25% or more of their capital controlled by sources located in Hong Kong, Macau or Taiwan as Chinese ethnic firms and firms with 75% or more of their capital owned by the government as state-owned firms. According to this classification 8.9% of the firms in the full sample are foreign, 9.4% are ethnic Chinese and 9.1% are state-owned. The remaining share of firms constitutes private domestic firms. Exporting firms are identified on the basis of their reported sales in foreign markets; a firm is marked as an exporter if we observe in the data exporting by the firm in any year within a 2-year moving window. All nominal monetary variables are converted into real values by deflating with the appropriate 2-digit industry deflators taken from the Chinese NBS. We use PPI to deflate sales and cost of materials, and asset price deflators for capital and fixed investment variables.[14]

The descriptive statistics of the main regression variables and important regional characteristics reported in Table 1 are calculated from the sample of all manufacturing

[13] In handling the Chinese firm data and calculating our regression variables we follow Brandt et al. (2012) and Zhang and Liu (2012).

[14] Katayama et al. (2009), De Loecker (2011) and related studies, point that a production function should be a mapping of data on input and output quantities. However, most studies tend to use revenue and expenditure data and apply industry level deflators for output, raw materials and capital assets to get back the quantity data needed. It is clear that inputs and outputs can be priced differently across firms within narrowly defined industries. This results in inconsistency discussed by Klette and Griliche (1996) in the case of common scale estimators. We note, however, that allowing for endogenous trade orientation in the unobservable (Rizov and Walsh 2009) and introducing location-specific information in the state space (Rizov and Walsh 2011) will control for persistent pricing gap across locations and between exporters and non-exporters in their use of inputs and their outputs within industries. Furthermore, Foster et al. (2005) find that productivity estimates from quantity and deflated revenue data are highly correlated and that the bias vanishes on average so that estimated average productivity is unaffected when aggregate deflators are used.

industries (1,754,672 observations in total) and represent firm averages. We compare average firm characteristics across our three regional typologies. In terms of population density, firms in less sparse areas compared to firms in the sparse areas are larger, older, invest and export more, and more of them are foreign owned. Firms in less sparse areas also are much more closely located to each other. The concentration of industries as measured by the market share of the top four industries (C4) is also much higher.[15] The composition of the top four industries differs importantly; in less sparse areas dominates manufacturing of electronic, electrical, transport and general purpose machinery and equipment. Sparse areas are dominated by manufacturing of chemicals, some transport machinery, basic metals and non-metallic minerals.

- Table 1 about here -

Considering the costal-inland typology, in terms of size (both assets and employment) inland firms are larger and invest more over the period of analysis.[16] Inland firms are also older which indirectly suggests that there has been an expansion of existing firms rather than relocation and creation of new firms. Coastal firms however are much more closely located to each other, export more and more of them are foreign owned. The C4 concentration index is similar across the two types of regions but the industry composition differs importantly. In coastal regions dominant are high-tech manufacturing of electronic and electrical machinery and equipment, some light industries such as textiles as well as chemical product industries. Inland, dominant are transport equipment, basic metals and heavy chemical industries, as well as tobacco products manufacturing.

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[15] We have also calculated the Herfindahl index for concentration of industries and it exhibits a very similar pattern to the C4 index. We prefer to report the C4 because we link it in the discussion to the composition of the top four industries in each regional category.

[16] Theory suggests that when regional wage differentials become large, investment should begin flowing to the regions with lower wages (Hu 2002). Such movement is being also encouraged in recent years in China by the government's "Western development initiative" which seems to have started affecting firm behavior in inland regions.

The rural-urban typology also reveals important differences across firms and industries. Firms in highly urbanized areas compared to their counterparts in mixed and rural areas are larger in terms of value added, employment, and capital, and invest more. Firms in highly urbanized areas are also more likely to export and to be owned by foreign investors. These characteristics are in accord with the firm density by location. Interestingly, industry concentration characterized by the C4 index is the highest in the less urbanized, rural areas – 45%. Dominant there are heavy industries such as basic metals and non-ferrous metals, non metallic minerals and heavy chemical production. In the urbanized, mixed areas the composition of dominant industries is quite diverse - a mixture of both heavy industries such as chemical and non metal mineral production and light industries such as food processing, while in highly urbanized areas, dominant are high-tech electronic and electrical industries, manufacturing of transport equipment and some metals.

Generally, there is similarity in firm and industry characteristics in the high density, less sparse, coastal and highly urbanized regions. A finding that stands out is that the inland firms appear to be larger and invest more than their coastal counterparts during the period of analysis. This might be due, on the one hand, to the inherent industrial structure and on the other, to the more recent convergence policies. Another interesting finding is the relatively high concentration of heavy metallurgy and chemical industries in the less urbanized, rural areas, characterized by very low firm density, and usually, scarce and highly specialized supporting infrastructure.

4 Estimation results

4.1 Productivity and regional disparities

In Table 2 we report average coefficients (using value added as weight) from the estimated 30 industry production functions by our three regional typologies. Coefficient estimates from each of the 30 industry regressions, number of observations and test statistics are reported in Appendix 2, Table A2 while the auxiliary results from estimating propensities to export and survive are available from the authors on request. The coefficients reported in Table 2 do not show substantial differences across regional categories. As expected, some variation is exhibited by the labor coefficients while capital coefficients are quite similar across all regional categories.

- Table 2 about here -

In Table 2 we also report, by our three regional typologies, average total factor productivity measures for the whole sample (TFP) and by exporting and ownership status of the domestic firms. Our results show that exporters (TFPE) are more productive than non-exporters (TFPN) as usually found in the literature. Private firms (TFPP) are more productive than state-owned firms (TFPS) as expected and the differences are quite striking. Furthermore, the average productivity measures also vary by category in all three regional typologies and clearly show that high density, less sparse, coastal and highly urbanized regions are the most productive. Average productivity is the highest in the less sparse, coastal (TFP of 2.511) and highly urbanized areas, with the highest of all TFPP of 2.608; average productivity is the lowest in the less urbanized, rural areas (TFP of 2.111), with the lowest of all TFPS of 0.915. These summary statistics confirm findings by numerous other studies that privatization and trade liberalization policies induce productivity.

Regional disparity is in the focus of the paper and we argued in the introduction that the regional productivity differences might be less pronounced than the regional differences in terms of wages and output. Therefore, next, we compare the regional disparities in TFP with disparities in wages (Wages) and output (Output) based on aggregates calculated by category for each regional typology using the full sample, which is also used by the NBS to estimate national GDP. In Table 3 we report differences between regional categories and the *p*-statistics of *t*-tests for significance of differences. We can observe in the table as expected that the TFP differences between regional categories are significant in every case and importantly, smaller than the wage and output differences for two of the typologies, by density of population and by level of urbanization. When costal vs. inland typology is considered disparities appear quite similar across the three measures. This might be due to the crude nature of the costal vs. inland typology which does not capture intra-province heterogeneity. Comparing the differences in the changes in productivity (ΔTFP), wages (ΔWages) and output (ΔOutput), we can observe consistent evidence of convergence, especially when the productivity measure is considered; changes in wages and output appear to vary less systematically.

- Table 3 about here -

4.2 Decomposition analysis

The evidence and discussion in previous sections suggest that there is a systematic relationship between productivity and the regional typologies we considered to capture regional disparities in China. Next, we analyze disparities in regional productivity by applying decompositions in levels and changes following Rice et al. (2006) and Rizov et al. (2012). Given our estimation strategy to directly build into the model of (unobserved) productivity all relevant factors affecting it, to demonstrate the link between regional disparities and productivity it is sufficient to use unconditional shift-share type decomposition.[17] Saito and Gopinath (2009) and Combes et al. (2012) identify the importance

[17] We also attempted multilevel regression analysis to cast light on the effects of the agglomeration forces on TFP following Van Oort et al. (2012). We estimated an equation with dependent variable our TFP measure and containing as explanatory variables firm-level, regional-level, and cross-level interaction terms for each category of our three regional typologies. All estimated effects are significant; firm size exhibits the usual inverted U-shaped pattern. The *urbanization* and *specialization* regional-level effects are of special interest. We find positive and significant specialization effect in every regional category while the urbanization effect systematically varies. It is positive in less sparse, coastal and highly urbanized regions while it turns negative for the rest of the regional categories. We argue that this finding suggests scarcity of appropriate infrastructure in the sparse, inland, rural regions which is consistent with our findings in previous sections of the paper. Given

of *agglomeration* forces and firm (and industry) *selection* for regional productivity. Therefore in the decompositions we consider these two factors as main sources of the spatial variation in regional productivity (productivity changes). First, differences in individual firm productivities (productivity changes) within each industry, resulting in different average productivities (productivity changes) across industries depend on the strength of various agglomeration effects. Second, differences in the industry composition within each regional category depend on firm (and industry) location choices driven by selection.[18]

We calculate for each of the three typologies aggregate industry productivity, q_u^n by regional category (u) and industry (n) as weighted average of individual firm TFPs (q_{jt}) using firm value added as weight.[19] The total value added in regional category u is denoted by $S_u = \Sigma_u s_u^n$ and the share of industry n in the total value added in regional category u is $\lambda_u^n = s_u^n/S_u$. The average productivity of industry n for the economy as a whole (i.e., aggregating across all regional categories u) is given by $\bar{q}^n = \sum_u s_u^n q_u^n / \sum_u s_u^n$, while $\bar{\lambda}^n = \sum_u s_u^n / \sum_u S_u$ is the share of industry n in total value added for the whole economy. Aggregate regional productivity q_u is weighted average of industry productivities in regional category u using industry value added shares as weights.

Regional productivity (a) can be decomposed as follows:

$$\underset{(a)}{q_u \equiv \sum_n q_u^n \lambda_u^n} \quad = \underset{(b)}{\sum_n q_u^n \bar{\lambda}^n} \quad + \underset{(c)}{\sum_n \bar{q}^n \lambda_u^n} \quad - \underset{(d)}{\sum_n \bar{q}^n \bar{\lambda}^n} \quad + \underset{(e)}{\sum_n (q_u^n - \bar{q}^n)(\lambda_u^n - \bar{\lambda}^n)}. \tag{9}$$

that the our focus is on estimating unbiased TFP measures and documenting the disparities between (aggregate) regional categories, we do not pursue further the multilevel regression analysis here; the detailed regression results are available on request.

[18] Ciccone and Hall (1996), Combes et al. (2012) and the related literature imply that the firm (and industry) selection can be seen as an outcome of a sorting equilibrium - that is, firms that value agglomeration highly locate in highly urbanized areas, firms that have high congestion costs are found in less urbanized, rural areas.

[19] Note that industry productivity is determined by individual firm productivities and firm market shares, within the industry, as discussed by Olley and Pakes (1996) and Rizov and Walsh (2009), among others. Thus, there could be two sources of industry productivity – within-firm productivity increases and reallocation of market shares towards more productive firms.

The first term on the right-hand side of Equation (9) is the average level of productivity in regional category *u* conditional on industry composition being the same as for the whole economy; we refer to this as *productivity index* (b). The second term is the average level of productivity of regional category *u* given its industry composition but assuming that the productivity of each industry equals the economy-wide average for that industry. It is referred to as the *industry composition index* (c). Remaining terms (d) and (e) measure the *residual covariance* between industry productivities and industry shares in regional category *u*. It is important to point out that comparison between productivity and industry composition indexes can provide useful information about the net impact of agglomeration and selection forces on regional productivity. The decomposition of productivity changes is analogous to the decomposition of productivity levels described above and further casts light on the sources of disparities in regional productivity.

We report productivity level decomposition results for the three typologies of the Chinese regions in Table 4, Panels A. While variation in aggregate productivity by regional category reflects differences in both productivity and industry composition, the spatial variation observed in the productivity index derives entirely from spatial variation in firm (industry) productivity and is independent of differences in industry composition. A higher value of the productivity index in a given regional category would suggest that industries in this category are more productive. The spatial variation in the industry composition index derives entirely from differences in the industry composition across regional categories and is independent of variation in industry productivity. A higher value of the industry composition index in a given category implies that the more productive industries are represented by larger industry shares in that regional category. The last covariance term in Equation (9) provides information about the link between industry shares and productivity; a positive sign of the term in a given regional category means that the more productive industries are also relatively larger indicating a positive regional specialization effect.

- Table 4 about here -

The results in Panels A are computed as averages for the 2000-2007 period and confirm that dense, less sparse, coastal and highly urbanized regional categories have the highest aggregate productivity. The sparse and inland regional categories lag behind in aggregate relative productivity by 8.3 and 27.8 percent respectively. The larger coastal-inland productivity difference suggests that besides density of economic activity there are other, policy and structural factors affecting productivity in Chinese regions. This assertion is further supported by the fact that in the rural-urban typology the urbanized, mixed category has a lower aggregate productivity than both the less urbanized, rural category and the highly urbanized category as the relative differentials are 4.0 and 7.1 percent respectively. It seems that as argued by Au and Henderson (2006a, 2006b) many of the medium sized cities located in urbanized, mixed areas are suboptimal in size due to restrictions in population mobility and suffer from below average productivity growth. At the same time less urbanized, rural areas, adjacent to large urban agglomerations and coastal regions as emphasized by Rozelle (1994) and Park (2008) have been favored most by the "Western development initiative" and policies for rural industrialization. These empirical findings are consistent with the Song et al.'s (2012) theoretical model of urbanization in China.

Productivity index exhibits a pattern where dense, less sparse, coastal and highly urbanized regional categories are monotonically more productive than the sparse, inland and urbanized, mixed categories while the less urbanized, rural category is characterized by the lowest productivity index. The pattern of the composition index is broadly the same as the pattern of the productivity index, except in the case of the rural-urban typology. There the less urbanized, rural category appears to have a more productivity inducing industry composition than the urbanized, mixed category. This is evidence of strong industry selection forces, possibly driven by government policies, affecting productivity in the less urbanized, rural areas. The covariance terms are generally quite small in magnitude and do not affect importantly aggregate productivity.

To explore further the factors affecting regional productivity we analyze the average annual productivity change over the 2000-2007 period following the decomposition defined in Equation (9) and report results in Table 4, Panels B. The period of analysis is generally characterized by a high annual productivity growth, of about 9.4 percent on average; this finding is in line with estimates by Brandt et al. (2012). The results in Panels B, however, show substantial heterogeneity in productivity growth by regional category for all three typologies. Considering the density of population typology, the growth is quite similar between the two categories. However, there is a substantial differential of 6.6 percent in the growth of the coastal-inland categories with inland regions exhibiting a higher growth over the period of analysis. For the rural-urban typology the growth pattern is quite interesting. Productivity in the less urbanized, rural category has risen most followed by the productivity in the highly urbanized category. Annual growth in the urbanized, mixed category lags behind by 6.0 percent from the less urbanized, rural category. This pattern also holds for both productivity and composition indexes but the largest differential is in terms of the composition index which has grown by 5.0 and 2.8 percent faster in less urbanized, rural category compared to the growth in the urbanized, mixed and highly urbanized categories respectively. This suggests that in the less urbanized, rural category a selected set of relatively productive industries have expanded substantially as well as further gained in productivity.

5 Conclusion

The focus of the paper is on evaluating the regional disparities in productivity of Chinese manufacturing using micro data. We build a structural model of the unobserved productivity emphasizing its link with trade and spatial density of economic activity and adapt the semi-parametric approach of Olley and Pakes (1996) to estimate the parameters of production functions, within 2-digit Chinese manufacturing industries, over the 2000-2007 period. We allow market conditions to vary by narrowly defined locations and model productivity as a second-order Markov process controlling for (endogenous) export status which greatly enhances our ability to obtain consistent estimates of the production function parameters and thus, back out unbiased firm-specific TFP measures. We aggregate the firm TFPs by the categories of three regional typologies designed to capture different dimensions of the regional disparities in China.

We find that regional productivity systematically differs across less sparse and sparse, coastal and inland, and highly urbanized, mixed and less urbanized, rural categories. Our findings are broadly consistent with the literature on regional income and output inequality, however, the magnitude of productivity disparities is smaller than the magnitudes exhibited by wages and output. Furthermore, we find that in recent years there have been substantial improvements in productivity of inland and less urbanized, rural areas. It seems that less urbanized, rural areas, adjacent to large urban agglomerations and coastal regions have benefited from the "Western development initiative" and policies for rural industrialization as asserted by Rozelle (1994) and Park (2008) leading to regional productivity convergence. At the same time many of the medium sized cities located in urbanized, mixed areas appear to have suffered below average productivity growth, possibly as a result of restrictions in population mobility as argued by Au and Henderson (2006b).

Taken together the results of our analysis provide evidence that there are factor market imperfections remaining in China which affect productivity and contribute to regional disparities. In the same time recent policies for infrastructure building and development of inland and western provinces seem to have been effective in achieving convergence across Chinese regions in terms of productivity. Therefore, there are good reasons to expect that regional income inequalities may also decline in the future. The implications of our analysis for policy are that besides enterprise focused privatization and export promotion, targeted regional development initiatives facilitating factor mobility have an important role to play in further improving productivity and reducing inequality in China.

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Table 1. Descriptive statistics by regional category

	VA	FA	IV	EM	AG	EX	EP	FR	C4	DS	No
Total sample	15306	15768	4703	195	8.72	0.25	0.23	0.16	40, 37, 32, 26	1.02	523789
	(129513)	(169429)	(41700)	(651)	(10.80)	(0.37)	(0.39)	(0.36)	(0.31)	(1.97)	
Population density											
High density	16477	16708	4989	203	8.77	0.24	0.24	0.18	40. 39, 37, 35	1.30	389693
	(138804)	(186626)	(66144)	(704)	(10.71)	(0.37)	(0.40)	(0.38)	(0.43)	(2.21)	
Low density (Sparse)	11896	13035	4258	173	8.58	0.26	0.18	0.11	26, 37, 32, 31	0.11	134096
	(97467)	(104411)	(33037)	(465)	(11.04)	(0.37)	(0.36)	(0.30)	(0.28)	(0.16)	
Coastal vs. inland provinces											
Coastal	14918	14378	4438	185	7.88	0.23	0.28	0.21	40, 39, 17, 26	1.28	368338
	(120385)	(166740)	(65376)	(572)	(9.58)	(0.36)	(0.42)	(0.39)	(0.34)	(2.25)	
Inland	16229	19062	5710	220	10.73	0.29	0.10	0.06	37, 32, 26, 16	0.32	155451
	(148988)	(175591)	(41612)	(807)	(13.03)	(0.38)	(0.26)	(0.23)	(0.33)	(0.67)	
Level of urbanisation											
Highly urbanized	16534	16809	5012	204	8.80	0.24	0.24	0.18	40, 37, 39, 32	1.30	391970
	(138710)	(186936)	(65967)	(709)	(10.74)	(0.37)	(0.40)	(0.38)	(0.33)	(2.20)	
Urbanized (Mixed)	12269	13066	4316	175	8.15	0.25	0.21	0.13	26, 31, 32, 13	0.13	98060
	(109296)	(98508)	(36113)	(473)	(10.53)	(0.38)	(0.38)	(0.32)	(0.30)	(0.14)	
Less urbanized	9842	11525	3740	157	9.44	0.30	0.09	0.05	32, 31, 33, 26	0.05	33759
(Rural)	(45072)	(106830)	(20367)	(310)	(12.05)	(0.38)	(0.26)	(0.21)	(0.45)	(0.08)	

Note: Mean and standard deviation (in parentheses) are reported for each variable. Abbreviations: VA - value added (thousands RMB); FA - total fixed assets (thousands RMB); IV - investment (thousands RMB); EM - Number of full-time equivalent employees; AG - firm age (years); EX - firm exits; EP - share of exporting firms; FR - share of foreign owned firms (combined ethnic Chinese and other foreign firms); C4 - list and market share (in parentheses) of the top 4 industries; DS - number of firms per km^2 (firm density); No - number of firms.

Table 2. Production function parameters and productivity estimates by regional category

	Labour	Capital	Age	Adj. R^2	TFP	TFPE	TFPN	TFPP	TFPS
Population density									
High density	0.670	0.377	-0.015	0.970	2.445	2.562	2.221	2.608	1.216
	(0.028)	(0.020)	(0.071)		(1.021)	(0.908)	(1.138)	(0.878)	(1.291)
Low density (Sparse)	0.672	0.376	-0.022	0.969	2.305	2.513	2.393	2.501	0.998
	(0.028)	(0.020)	(0.068)		(1.093)	(0.931)	(1.067)	(0.904)	(1.338)
Coastal vs. inland provinces									
Coastal	0.668	0.376	-0.018	0.970	2.511	2.573	2.475	2.606	1.243
	(0.028)	(0.020)	(0.068)		(0.960)	(0.884)	(1.003)	(0.851)	(1.289)
Inland	0.680	0.379	-0.026	0.967	2.164	2.193	2.111	2.499	1.067
	(0.029)	(0.020)	(0.068)		(1.182)	(1.120)	(1.197)	(0.986)	(1.323)
Level of urbanisation									
Highly urbanized	0.671	0.377	-0.019	0.969	2.447	2.512	2.391	2.608	1.212
	(0.028)	(0.020)	(0.068)		(1.022)	(0.931)	(1.069)	(0.879)	(1.291)
Urbanized (Mixed)	0.673	0.375	-0.023	0.968	2.379	2.592	2.291	2.532	1.050
	(0.028)	(0.020)	(0.068)		(1.050)	(0.891)	(1.098)	(0.877)	(1.330)
Less urbanized	0.681	0.375	-0.030	0.967	2.111	2.378	2.067	2.404	0.915
(Rural)	(0.030)	(0.021)	(0.067)		(1.184)	(1.001)	(1.209)	(0.978)	(1.354)

Note: Average coefficients and standard errors (in parentheses) over the respective estimates from 30 industry production functions are reported. TFP is an average productivity measure over all firms in the respective regional category. TFPE and TFPN denote the TFP of exporter and non-exporter firms respectively. TFPP and TFPS denote the TFP of private and state firms respectively.

Table 3. Regional disparities in productivity, wages, and output

	TFP	Wages	Output	ΔTFP	ΔWages	ΔOutput
Population density						
High – Low	0.140	0.212	0.209	-0.027	-0.022	-0.038
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Coastal vs. inland provinces						
Coastal - Inland	0.346	0.331	0.279	-0.026	-0.002	-0.003
	(0.000)	(0.000)	(0.000)	(0.000)	(0.118)	(0.073)
Level of urbanisation						
HU - U	0.067	0.140	0.148	-0.026	-0.024	-0.043
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
U - LU	0.264	0.282	0.274	-0.018	0.004	0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.255)	(0.755)
HU - LU	0.331	0.422	0.422	-0.044	-0.020	-0.042
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Note: TFP is an average productivity measure over all firms in the respective regional category. The *p*-values for the *t*- tests of mean difference between regional categories are reported in parentheses. Abbreviations: HU – highly urbanized; U – urbanized; LU – less urbanized; Δ denotes change.

Table 4. Regional productivity decompositions

	Aggregate productivity	Productivity index	Composition index	Residual covariance	
	(a)	(b)	(c)	(d)	(e)
Population density					
Panel A: Average levels, 2000-2007					
High density	1.062	1.030	1.041	1.000	-0.009
Low density (Sparse)	0.979	0.993	0.986	1.000	0.000
Panel B: Annual changes, 2000-2007					
High density	0.080	0.088	0.088	0.094	-0.002
Low density (Sparse)	0.092	0.096	0.090	0.094	0.001
Coastal vs. inland provinces					
Panel A: Average levels, 2000-2007					
Coastal	1.087	1.030	1.062	1.000	-0.005
Inland	0.809	0.950	0.864	1.000	-0.005
Panel B: Annual changes, 2000-2007					
Coastal	0.071	0.084	0.081	0.094	-0.001
Inland	0.137	0.122	0.116	0.094	-0.007
Level of urbanisation					
Panel A: Average levels, 2000-2007					
Highly urbanized	1.012	1.005	1.008	1.000	-0.001
Urbanized (Mixed)	0.941	0.985	0.957	1.000	-0.001
Less urbanized (Rural)	0.981	0.963	1.005	1.000	0.013
Panel B: Annual changes, 2000-2007					
Highly urbanized	0.096	0.094	0.096	0.094	0.000
Urbanized (Mixed)	0.074	0.093	0.074	0.094	0.001
Less urbanized (Rural)	0.134	0.111	0.124	0.094	-0.006

Note: For definitions of the decomposition components refer to Equation (9) in the text. Values reported in Panel A for each sample are normalized by the covariance term $\sum_n \bar{q}^n \bar{\lambda}^n$ from Equation (9). Component (d) has a negative sign in all decompositions.

Appendix 1

Theoretical foundations of the Olley and Pakes (1996) algorithm

The single period profit function of firm *j* at time *t* is $\pi(k_{jt}, a_{jt}, \omega_{jt}, r_t) - c(i_{jt}, r_t)$, where k_{jt}, a_{jt} and ω_{jt} are the logs of firm's state variables, capital, age, and (unobserved) productivity respectively, while i_{jt} is the log of firm's investment. Both restricted profit π(.) and adjustment cost c(.) depend also on r_t, which represents the economic environment that firms face at a particular point in time; r_t captures effects of input prices, demand conditions, industry characteristics and all these factors are assumed to change over time.

The incumbent firm maximizes its expected value of both current and future profits according to:

$$V(k_{jt}, a_{jt}, \omega_{jt}, r_t) = \max\begin{cases} \Phi(k_{jt}, a_{jt}, \omega_{jt}, r_t), \\ \max_{i_{jt}\geq 0}\{\pi(k_{jt}, a_{jt}, \omega_{jt}, r_t) - c(i_{jt}, r_t) + \\ \beta E[V(k_{jt+1}, a_{jt+1}, \omega_{jt+1}, r_{t+1}) \mid k_{jt}, a_{jt}, \omega_{jt}, r_t, i_{jt}]\}. \end{cases} \tag{A1}$$

The Bellman equation explicitly considers two firm decisions. First is the exit decision; $\Phi(k_{jt}, a_{jt}, \omega_{jt}, r_t)$ represents the sell-off value of the firm. Second is the investment decision i_{jt}, which solves the interior maximization problem. Under the assumption that equilibrium exists and that the difference in profits between the firm continuing and exiting is increasing in ω_{jt} we can write the optimal exit decision rule as

$$\mathrm{X}_{jt} = \begin{cases} 1 & if \quad \omega_{jt} \geq \overline{\omega}_t(k_{jt}, a_{jt}) \\ 0 & \qquad otherwise \end{cases} \tag{A2}$$

and the investment demand function as

$$i_{jt} = i_t(k_{jt}, a_{jt}, \omega_{jt}, r_t). \tag{A3}$$

The (structural) model of the unobserved productivity is derived by inverting the investment demand function (Equation A3) to generate a proxy for unobserved productivity:

$$\omega_{jt} = h_t(i_{jt}, r_t, k_{jt}, a_{jt}). \tag{A4}$$

Thus, the productivity of a firm j at time t is specified as a function of the firm's state variables (capital k_{jt} and age a_{jt}), investment i_{jt}, and the economic environment characteristics that the firm faces at a particular point in time r_t. The function is treated non-parametrically in the estimation algorithm. Investment demand traces (expected) productivity and serves as the main control variable.

Appendix 2

Table A1. Manufacturing industries in China

IND2	Definition
13	Food processing
14	Manufacturing of food
15	Manufacturing of beverages
16	Manufacturing of tobacco products
17	Manufacturing of textiles
18	Manufacturing of wearing apparel
19	Tanning & dressing of leather
20	Manufacturing of wood and products of wood
21	Manufacturing of furniture
22	Manufacturing of pulp paper and paper product
23	Publishing and printing
24	Manufacturing of sports goods, musical instruments, toys and stationers goods
25	Manufacturing of coke and refined petroleum
26	Manufacturing of chemicals and chemical products
27	Manufacturing of pharmaceutical goods
28	Manufacturing of man-made fibers
29	Manufacturing of rubber products
30	Manufacturing of plastic products
31	Manufacturing of other non metallic minerals
32	Manufacturing of basic metals
33	Manufacturing of non-ferrous metals
34	Manufacturing of other metals
35	Manufacturing of general purpose machinery and equipment
36	Manufacturing of special purpose machinery and equipment
37	Manufacturing of transport equipment and products
39	Manufacturing of electrical machinery
40	Manufacturing of communication, computer and other electronic equipment
41	Manufacturing of medical and optical instruments and office machinery
42	Manufacturing of artworks and crafts
43	Recycling

Note: IND2 indicates 2-digit industry code.

Table A2. Production function coefficient estimates within 2-digit industries

IND2		Parameters	IND2		Parameters	IND2		Parameters
(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
13	b_l	0.69	14	b_l	0.66	15	b_l	0.72
	s.e.	0.02		s.e.	0.03		s.e.	0.04
	b_k	0.35		b_k	0.38		b_k	0.46
	s.e.	0.02		s.e.	0.03		s.e.	0.04
	b_a	-0.09		b_a	-0.06		b_a	-0.07
	s.e.	0.09		s.e.	0.05		s.e.	0.08
	R^2	0.96		R^2	0.96		R^2	0.96
	No	11332		No	4789		No	3948
16	b_l	0.65	17	b_l	0.66	18	b_l	0.63
	s.e.	0.21		s.e.	0.02		s.e.	0.02
	b_k	0.39		b_k	0.33		b_k	0.32
	s.e.	0.04		s.e.	0.01		s.e.	0.02
	b_a	0.03		b_a	-0.02		b_a	-0.01
	s.e.	0.07		s.e.	0.05		s.e.	0.05
	R^2	0.98		R^2	0.97		R^2	0.98
	No	344		No	18423		No	10096
19	b_l	0.56	20	b_l	0.69	21	b_l	0.70
	s.e.	0.03		s.e.	0.03		s.e.	0.04
	b_k	0.32		b_k	0.29		b_k	0.38
	s.e.	0.02		s.e.	0.02		s.e.	0.03
	b_a	-0.04		b_a	-0.03		b_a	-0.03
	s.e.	0.05		s.e.	0.08		s.e.	0.09
	R^2	0.98		R^2	0.97		R^2	0.97
	No	4981		No	5248		No	2051
22	b_l	0.76	23	b_l	0.68	24	b_l	0.62
	s.e.	0.04		s.e.	0.04		s.e.	0.04
	b_k	0.26		b_k	0.42		b_k	0.21
	s.e.	0.02		s.e.	0.03		s.e.	0.02
	b_a	0.04		b_a	-0.02		b_a	-0.02
	s.e.	0.15		s.e.	0.08		s.e.	0.06
	R^2	0.97		R^2	0.97		R^2	0.98
	No	7339		No	5282		No	3023
25	b_l	0.40	26	b_l	0.65	27	b_l	0.66
	s.e.	0.08		s.e.	0.03		s.e.	0.02
	b_k	0.51		b_k	0.36		b_k	0.37
	s.e.	0.05		s.e.	0.02		s.e.	0.01
	b_a	0.06		b_a	0.01		b_a	-0.03
	s.e.	0.04		s.e.	0.07		s.e.	0.03
	R^2	0.98		R^2	0.97		R^2	0.97
	No	1327		No	16901		No	23262

Table A2. Continued

(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
28	b_l	0.60	29	b_l	0.60	30	b_l	0.55
	s.e.	0.08		s.e.	0.05		s.e.	0.02
	b_k	0.34		b_k	0.37		b_k	0.44
	s.e.	0.07		s.e.	0.05		s.e.	0.02
	b_a	0.07		b_a	0.21		b_a	-0.01
	s.e.	0.04		s.e.	0.58		s.e.	0.08
	R^2	0.98		R^2	0.97		R^2	0.98
	No	816		No	2343		No	9245
31	b_l	0.62	32	b_l	0.87	33	b_l	0.76
	s.e.	0.02		s.e.	0.06		s.e.	0.06
	b_k	0.44		b_k	0.26		b_k	0.42
	s.e.	0.02		s.e.	0.02		s.e.	0.04
	b_a	-0.04		b_a	-0.04		b_a	-0.03
	s.e.	0.03		s.e.	0.06		s.e.	0.09
	R^2	0.97		R^2	0.95		R^2	0.96
	No	20403		No	3728		No	3073
34	b_l	0.56	35	b_l	0.69	36	b_l	0.81
	s.e.	0.02		s.e.	0.02		s.e.	0.04
	b_k	0.38		b_k	0.42		b_k	0.38
	s.e.	0.02		s.e.	0.01		s.e.	0.03
	b_a	-0.01		b_a	-0.01		b_a	-0.04
	s.e.	0.07		s.e.	0.05		s.e.	0.07
	R^2	0.98		R^2	0.98		R^2	0.96
	No	9103		No	14588		No	7165
37	b_l	0.79	39	b_l	0.59	40	b_l	0.68
	s.e.	0.03		s.e.	0.02		s.e.	0.03
	b_k	0.35		b_k	0.46		b_k	0.36
	s.e.	0.02		s.e.	0.02		s.e.	0.02
	b_a	-0.02		b_a	-0.02		b_a	-0.04
	s.e.	0.05		s.e.	0.07		s.e.	0.10
	R^2	0.96		R^2	0.98		R^2	0.97
	No	10263		No	12556		No	6828
41	b_l	0.77	42	b_l	0.60	43	b_l	0.49
	s.e.	0.06		s.e.	0.03		s.e.	0.04
	b_k	0.22		b_k	0.29		b_k	0.46
	s.e.	0.05		s.e.	0.02		s.e.	0.13
	b_a	-0.04		b_a	-0.01		b_a	0.08
	s.e.	0.17		s.e.	0.08		s.e.	0.14
	R^2	0.96		R^2	0.98		R^2	0.99
	No	2921		No	3796		No	123

Note: Reported R^2 statistics and number of observations (No) are from the last step of the estimation algorithm. IND2 denotes 2-digit industry code.