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CONTENTS

(*continued on outside back cover*)

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Export Upgrading and Growth: The Prerequisite of Domestic Embeddedness

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Summary. — Our work contributes to the literature relating output structure and economic development by showing that growth gains from upgrading are not unconditional. Relying on data from a panel of Chinese cities, we show that the level of capabilities available to domestic firms operating in ordinary trade is an important driver of economic growth. However, no direct gains emanate from the complexity of goods produced by either processing-trade activities or foreign firms. This suggests that the sources of product upgrading matter, and that domestic embeddedness is key in order for capacity building and technology adoption to be growth enhancing.

Key words — economic complexity, export upgrading, FDI, processing trade, growth, China

1. INTRODUCTION

Recent empirical work has put structural transformation back to the forefront of the understanding of economic growth (Hausmann & Hidalgo, 2011). Differences in countries' ability to upgrade their production and diversify into complex goods appear to explain why they take off or remain poor (McMillan & Rodrik, 2011). According to Hidalgo and Hausmann's theory of capabilities, a country's capacity to grow resides in the diversity of its available capabilities. Numerous and exclusive capabilities are required to move toward new activities associated with higher productivity levels.[1] A by now well-established empirical result is that countries specializing in more sophisticated goods subsequently grow faster (Hausmann, Hwang, & Rodrik, 2007; Hidalgo & Hausmann, 2009; Rodrik, 2006). This result has logically revived the question of which policy measures can help countries to produce these higher productivity goods.

The attraction of FDI inflows has often been contemplated as one powerful tool to promote quality upgrades to the country product structure. The first channel is direct since the quality of goods produced by foreign-invested firms is typically higher than those previously exported by domestic firms in the host country (Iacovone & Javorcik, 2010; Wang & Wei, 2010).[2] Second, the presence of multinationals may facilitate the product upgrading of domestic firms through various spillovers. Similar theoretical arguments apply to the promotion of processing trade, which involves the assembly of imported inputs into a final good for export. Apart from the direct effect of producing more sophisticated goods, processing trade may generate knowledge spillovers within firms[3] and between firms. However there are a number of factors which may undermine these potential technological spillovers in practice, especially in the context of developing countries (Crespo & Fontoura, 2007). Technology diffusion and adoption may fail to come about due to limited domestic absorption capacity or in the absence of substantial and well-directed technological efforts by foreign and domestic firms (Lall, 1992, 2001). An additional related impediment is that foreign technologies may not be appropriate to the economic and social conditions of developing countries (Basu & Weil, 1998). The available empirical literature on spillovers from FDI reflects this theoretical ambiguity and finds mixed results (Blomström, Kokko, & Globerman, 2001; Görg & Strobl, 2001). The absence of the expected spillovers has important repercussions on the sophistication–growth nexus: the apparent upgrading of a country's exports could be a statistical mirage. This could only reflect the advances of foreign firms or processed inputs and not signal any enhanced capacity to produce (and export) more complex products by domestic firms. In this case the growth benefits could be zero.

This paper argues that the sources of product upgrading matter and that domestic embeddedness is key for capacity building and technology adoption to be growth enhancing. Our empirical results suggest that China's approach to internationalization based on the confinement of foreign investment in tax-favored special economic zones and in processing trade activities has prevented the capabilities of foreign firms from being growth-enhancing. Our work contributes to the literature relating output structure and economic development by showing that the growth gains from upgrading are not unconditional. Relying on data from a panel of

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Chinese cities, we show that there are no direct gains from the complexity of goods produced by either processing-trade activities or foreign firms. Our results are in line with Jarreau and Poncet (2012) who find that the growth enhancement from export sophistication is limited to the ordinary export activities undertaken by domestic firms. Our approach is different in two respects: first, we depart from the cross-section analysis of city performance and rely on panel data estimates which have the advantage of mitigating the omitted-variables problem via fixed effects. We also rely on a series of robustness checks to ensure that our results are not driven by measurement or endogeneity biases, including long difference in cross-section, first difference and GMM-system estimators. Second, upgrading is measured using the newest Hidalgo and Hausmann (2009) indicator of economic complexity instead of Hausmann *et al.*'s (2007) measure of the income level of an export basket. The economic complexity variable aims to capture the number and exclusivity of locally-available capabilities. It is calculated using the method of reflections developed by Hidalgo and Hausmann (2009) so as to answer the criticism addressed to the circularity of the Hausmann *et al.* (2007) measure of export sophistication (Felipe, Kumar, Abdon, & Bacate, 2012). The problem with export sophistication is that it is measured by comparison to the income level of countries with similar export structures, mechanically leading to the circular conclusion that "rich countries export rich-country products." By contrast, Hidalgo and Hausmann's (2009) economic complexity measure separates information on income from that on the network structure of countries and the products they export.

We compute economic complexity for a panel of over 200 Chinese cities and show that it is a much more robust determinant of economic growth than is export sophistication. When jointly included in a growth regression, export sophistication becomes insignificant while economic complexity is positively and significantly associated with faster subsequent GDP per capita growth. Our results hence confirm, in the context of a panel of cities within one single country (China), Hidalgo and Hausmann's (2009) prediction that deviations from the correlation between economic complexity and income are good predictors of future growth. We find that locations with productive structures geared toward complex products enjoy higher subsequent economic growth, controlling for the level of income. We do however show that the result pertains exclusively to the capabilities of firms which are well-embedded in the local economy. As our data differentiate between processing and ordinary trade separately for domestic and foreign-owned firms, we are able to compute the growth benefits for those four respective categories of export upgrading. The research here hence further contributes to the literature in two different ways.

We first add insights into the potential role of processing trade and FDI in development strategies. These confirm existing results on the effectiveness of China's FDI-reliant industrial and trade strategy. For instance, Wang and Wei (2010) find that neither processing trade nor foreign-invested firms can explain the increased overlap in the export structure between China and high-income countries. [4] Our result that economic complexity only boosts growth if it is locally embedded is in line with the suggestion in Wang and Wei (2010) that the key to China's evolving export structure is human-capital accumulation and favorable government policies such as tax-favored high-tech zones. This casts doubt on the capacity of China (as well as developing countries in general) to successfully build up their own growth-enhancing capabilities through technology acquisition via assembling activities and foreign investment. Our message is thus consistent with the observation made by Fu, Pietrobelli, and Soete (2011) regarding developing countries, that international technology diffusion does not unconditionally follow from globalization and liberal trade regimes. As shown by Lall (2003), the expected gains via technological transfers from FDI-based strategies do not materialize systematically. They instead require a complex mix of indigenous innovation efforts and the presence of appropriate institutions and innovation systems. In the case of China, we interpret our results as evidence that structural and geographical disconnections between ordinary activities and those based on imported technology and foreign affiliates can impede technological diffusion. Similar arguments are brought up in the literature (Blonigen & Ma, 2007; Hale & Long, 2011; Lemoine & Unal-Kesenci, 2004) to explain the limited impact of assembly trade on local production and the absence of FDI spillovers on the productivity of Chinese domestic firms. Chinese authorities have adopted an "enclave" approach to internationalization, confining foreign investment and processing activities to special economic zones dedicated to export development. Our findings suggest that this deliberate choice, by limiting local embeddedness, has reduced potential spillovers and hampered the emergence of growth gains from processing and foreign activities.

Our results further contribute to the literature highlighting the specificity of processing trade. Recent empirical evidence has emphasized, most often in the context of China, that processing trade is a different activity from nonprocessing trade (Dai, Maitra, & Yu, 2011; Manova & Yu, 2012). [5] Our finding of a relationship between export upgrading and economic growth which depends on whether capabilities are embedded in processing activities further confirms that distinguishing between processing and ordinary exporters is crucial for our understanding of trade performance and growth potential. This would also seem to confirm the claims that processing trade systematically upwardly distorts the "true" level of Chinese export sophistication (Amiti & Freund, 2010; Van Assche & Gangnes, 2010; Yao, 2009). Our results here suggest that the upgrading of ordinary export activities by domestic firms is the key indicator of the genuine adoption of technology at the local level and to predict benefits in terms of economic growth.

The remainder of the paper is structured as follows. In the next section we set out our measure of complexity and the datasets used. Section 3 then presents our empirical approach, results and robustness checks. Last, Section 4 concludes.

2. DATA AND MAIN VARIABLES

(a) *Product complexity*

Following the literature on economic complexity (or sophistication), we calculate a location's complexity as a weighted average of the complexity of the products it exports. The weighting reflects the relative importance of each product in the local export basket. The capacity of a locality to export many complex products is considered to be indirect evidence of the available local capabilities. The direct determination of intrinsic product features (the technology embedded in it, the specialized skills required to produce it, R&D investments, and so on) is difficult, especially at a very detailed level. [6] Most indicators (Hausmann *et al.*, 2007; Hidalgo & Hausmann, 2009) instead infer the complexity of the products from observed worldwide trade patterns.

Hausmann *et al.* (2007) identify sophisticated goods as those requiring greater levels of development to be exported. [7] They capture the sophistication level (they call it "productivity") of a good k by reference to the income level of the countries

which export it. They propose the indicator $PRODY_k$ which is the weighted average of the income levels of good k's exporters, where the weights correspond to the revealed comparative advantage of each country j in good k:

$$PRODY_k = \sum_j \left[\frac{x_{jk}/X_j}{\sum_j x_{jk}/X_j} \right] \times Y_j \tag{1}$$

Here x_{jk} is the value of exports of good k by country j, X_j the total value of country j's exports, and Y_j the per capita income of country j, measured as the real GDP per capita in PPP. The greater is the weight of good k in the exports of rich countries, the higher is its $PRODY$, the more sophisticated it is considered to be. This indicator's use of income information has been criticized as it gives rise to a circularity issue that "rich countries export rich-country products" (Hidalgo, 2009).

Hidalgo and Hausmann (2009) address this problem by proposing a complexity indicator that is based solely on information on the network structure of countries and the products they export. They argue that a complex product is one that requires many or exclusive capabilities. This exclusivity of the set of capabilities used by a product can then be inferred from its ubiquity and from the diversity of the export basket of the countries that export it. Complex products are expected to be exported by fewer countries with Revealed Comparative Advantage (RCA) (i.e., they are less ubiquitous) and by countries with many and diverse capabilities.[8]

Hidalgo and Hausmann (2009) develop the method of reflections that consists in calculating jointly and iteratively the ubiquity and the diversity indicators to introduce in the product complexity measure as much information as possible from the network structure of countries and products.

Ubiquity and diversity are computed as follows:

$$UBIQUITY_k = K_{k,0} = \sum_j M_{jk} \tag{2}$$

$$DIVERSITY_j = K_{j,0} = \sum_k M_{jk} \tag{3}$$

where j denotes the country, k the product, and $M_{j,k}$ is equal to 1 if country j exports product k with revealed comparative advantage and 0 otherwise.[9] The index of Revealed Comparative Advantage (RCA) is defined following Balassa (1964) as the ratio of the export share of a given product in the country's export basket to the same share at the worldwide level:

$$RCA_{jk} = \frac{x_{jk}/X_j}{\sum_j (x_{jk}/X_j)} \tag{4}$$

Product complexity for good k is hence computed after n iterations as the following weighted average:

$$K_{k,n} = \frac{1}{K_{k,0}} \sum_j M_{jk}\ K_{j,n-1} \tag{5}$$

where $K_{j,n-1}$ is economic complexity defined at the country-j level:

$$K_{j,n-1} = \frac{1}{K_{j,0}} \sum_k M_{jk}\ K_{k,n-2} \tag{6}$$

To clarify the logic behind the iterations, consider the benefits of moving from $K_{k,0}$ (ubiquity) to $K_{k,1}$ to evaluate the complexity of good k. Compared to $K_{k,0}$, $K_{k,1}$ shows that a complex good is not only characterized by a low level of ubiquity ($K_{k,0}$) but also by being exported by complex countries (i.e., those with high diversity), it hence corresponds to the average diversity[10] of the countries that export k with RCA, which is computed as:

$$K_{k,1} = \frac{1}{K_{k,0}} \sum_j M_{jk}\ K_{j,0} \tag{7}$$

Similarly the complexity of a country should not only be viewed as related to diversity but should also reflect the degree of ubiquity of the products that it exports, which corresponds to:

$$K_{j,1} = \frac{1}{K_{j,0}} \sum_k M_{jk}\ K_{k,0} \tag{8}$$

Additional information regarding the complexity of the product k can hence be extracted from an additional iteration, that is, $K_{k,2}$, which is the average $K_{j,1}$ of countries exporting k with RCA. This corresponds to the average ubiquity of the products exported with RCA by countries exporting product k with RCA. The same logic applies to the iterations of the measure of country-level complexity. The indicator $K_{j,2}$ refines the evaluation of country-level complexity compared to $K_{j,1}$ by computing the average diversity of countries with similar export baskets to country j.

Eqn. (5) is iterated until no additional information can be derived from the previous iteration, that is when the relative rankings of the values estimated using (5) in the $n + 1$th and nth iterations are the same.[11]

We compute product complexity for 5017 products using the BACI world trade dataset. This covers trade at the 6-digit product level for 230 countries.[12] Our product complexity measure corresponds to the 15th iteration, $K_{k,15}$, for 1997, the first year of our panel. Using a time-invariant measure of product complexity reduces the likelihood of bias in the index as it ensures that our measure of the capability requirements of products is not affected by economic changes over time, such as the rise of China in international trade or other evolutions in the world-trade structure. However, as a robustness check, we will ensure that our results continue to hold when we use a time-varying measure.

(b) *City complexity*

We compute economic complexity for over 200 cities in China: this is the average complexity of the goods that the city exports with revealed comparative advantage.

Using the above notation from Hidalgo and Hausmann (2009) and indexing cities by c, we calculate the city complexity index K_c as:

$$K_c = \frac{1}{K_{c,0}} \sum_k M_{c,k}\ K_{k,15} \tag{9}$$

where $M_{c,k}$ is a dummy variable taking the value 1 if city c has a comparative advantage in the good k, $K_{c,0}$ is the number of products for which city c has a comparative advantage, and $K_{k,15}$ is product-level complexity as defined above. We use Chinese customs data over the 1997–2007 period, which report exports by 6-digit product.[13] One feature of interest in this dataset is that it separates trade flows depending on the ownership type of the exporter (foreign or domestic) and the trade regime. This allows us notably to investigate the specificity of processing trade. It is officially defined as "*business activities in which the operating enterprise imports all or part of the raw or ancillary materials, spare parts, components, and packaging*

materials, and re-exports finished products after processing or assembling these materials/parts." [14]

Following Hausmann *et al.* (2011), we use the standardized version of our indicator to consider the link between complexity and economic growth. For a given city c and year t, complexity is calculated as the value of K_c^t minus the yearly average across the n Chinese cities in our sample, [15] all divided by the yearly standard deviation. [16]

$$Complexity_c^t = \frac{K_c^t - \sum_c K_c^t / n}{\sigma_{K_c^t}} \tag{10}$$

Figure 1 provides a visual summary of the relationship between GDP per capita growth and complexity in Chinese cities. We use data on GDP per capita growth during 1997–2009 split into three 4-year sub-periods after controlling for the log of initial GDP per capita, year fixed effects and city fixed effects.

We contrast the results in panel (a) obtained using our indicator à la Hausmann *et al.* (2011) to those based on the export-sophistication indicator proposed by Hausmann *et al.* (2007), reported in panel (b).

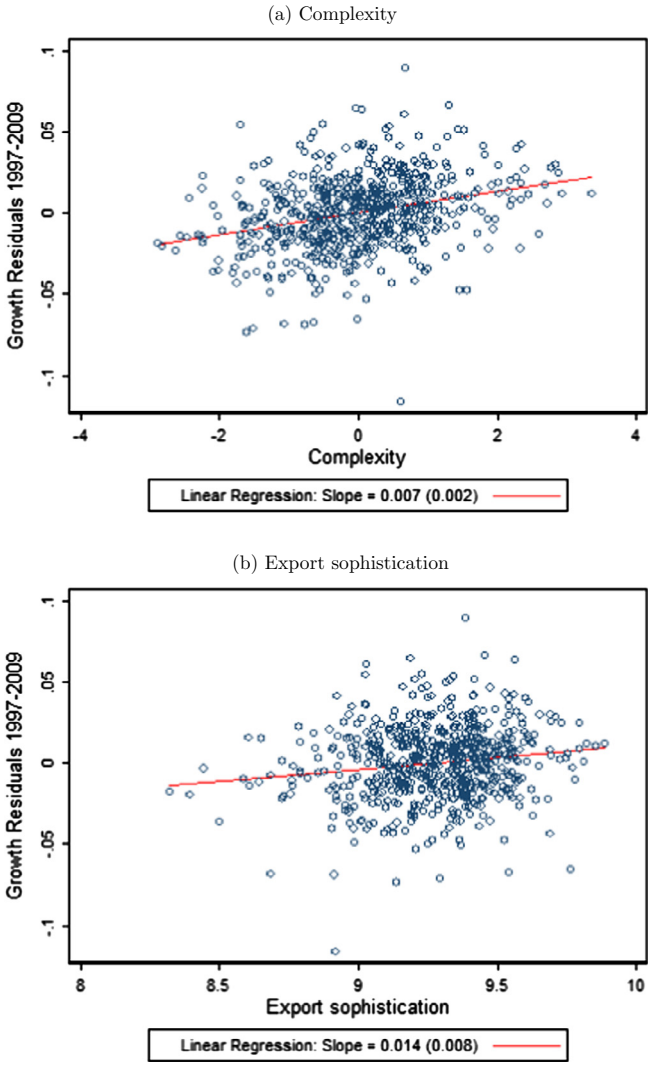

Figure 1. *Complexity and GDP per capita growth across Chinese cities. Note: Chinese prefecture complexity or sophistication and GDP per capita growth during 1997–2009 (3× 4-year sub-periods) after controlling for Ln initial GDP per capita, year fixed effects and city fixed effects.*

We find for both indicators the expected positive and significant relationship between upgrading and economic growth. The correlation appears to be stronger for the Hausmann *et al.* (2011) complexity indicator as indicated by the steeper slope and a smaller standard error.

Figure 2 decomposes complexity into its four components depending on firm-ownership type (domestic or foreign) and trade regime (domestic or processing). The components are calculated from Eqn. (9) using the specific export baskets of domestic and foreign firms under the processing and ordinary trade regimes. There is a clear positive relationship between complexity and GDP per capita growth in panel (a) for domestic firms engaged in ordinary trade. The relationship is insignificant in the other panels, providing some preliminary evidence that the source of complexity is important for upgrading to be growth-enhancing.

Macro-level data at the city level, including GDP, population, and traditional determinants of growth such as investment, human capital, or FDI, are taken from China Data Online, provided by the University of Michigan. Combining the customs and macro-level data, we end up with a sample of 221 cities for which we have consistent data on GDP per capita and export structure during 1997–2009. The list of these cities appears in Appendix Table 8. The summary statistics for all variables are presented in Table 9 and their pairwise correlations appear in Table 10.

3. EMPIRICAL ESTIMATION

(a) *Baseline specification*

We would like to establish the empirical link between initial complexity and subsequent GDP per capita growth in Chinese cities, controlling for initial income and the traditional determinants of economic growth (Barro, 1991). Our baseline specification comes from a fixed-effect estimation using our city-level panel data, of the following form:

$$\begin{aligned}\frac{Y_{c,t+4} - Y_{c,t}}{4} &= \alpha_0 + \alpha_1 Y_{c,t} + \beta\ Complexity_{c,t} \\ &\quad + \gamma_1 InvRate_{c,t} + \gamma_2 HumCap_{c,t} \\ &\quad + \gamma_3 Openness_{c,t} + \gamma_4 FDI_{c,t} + \eta_c + \mu_t + \epsilon_c \end{aligned} \tag{11}$$

where Y denotes log GDP per capita and c is the index of our 221 cities. In Table 1, we estimate this model for three 4-year sub-periods starting in 1997 (1997–2000, 2001–04, and 2005–09). The *Complexity* variable proxies for the number and exclusivity of capabilities in the city, as discussed in Section 2. We include the logarithm of initial GDP per capita since we focus on the growth predictive power of deviations from the correlation between economic complexity and income. The ratio of investment in fixed assets to GDP (*InvRate*) is a proxy for the rate of physical capital accumulation, and the share of population enrolled in secondary schooling to control for human capital in the city's labor force (*HumCap*). We also include the openness rate (imports plus exports over GDP) and FDI inflows over GDP in the city, as suggested by Berthélemy and Démurger (2000) in the Chinese context. Last, the regressions contain both city and time dummies, denoted by η_c and μ_t respectively. The econometric issues resulting from the use of fixed effects in a growth model with a lagged dependent variable are explored in the next subsection. This will discuss various robustness checks, including a long difference (1997–2009) in GDP per capita growth as in Hausmann *et al.* (2007) and the use of first-difference and GMM system estima-

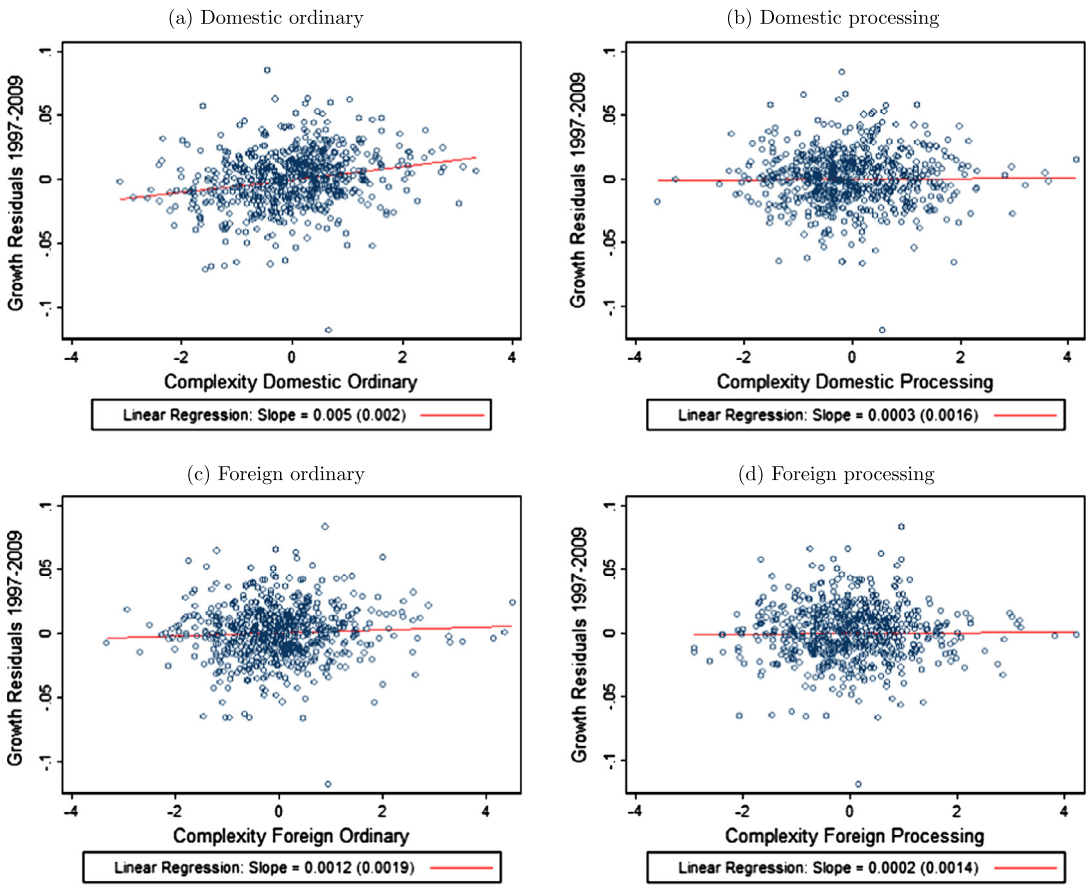

Figure 2. *Four components of complexity and GDP per capita growth across Chinese cities. Note: Chinese prefecture complexity and GDP per capita growth during 1997–2009 (3× 4-year sub-periods) after controlling for Ln initial GDP per capita, year fixed effects and city fixed effects.*

tors. These latter two approaches are used to address the problem of omitted variables in panel data regressions.[17]

Our departure point in column 1 of Table 1 appeals to export sophistication from Hausmann *et al.* (2007) as a proxy for complexity. This hence corresponds to the panel equivalent of the cross-section results in Jarreau and Poncet (2012). The coefficient on export sophistication is positive as expected, but significant at the 10% confidence level only. This estimated coefficient becomes insignificant when we use our preferred complexity indicator in column 2. The indicator of complexity in Hausmann *et al.* (2011) is however significant at the 1% confidence level and is robust to the inclusion of numerous controls, as shown in columns 3–7 of Table 1. We interpret this result as showing the greater capacity of the complexity indicator to capture the time-varying level and diversity of capabilities across Chinese cities.

The coefficients on the control variables are as expected. Initial GDP per capita enters with a negative and significant coefficient, indicating a process of conditional income convergence across Chinese cities. Our measure of physical-capital accumulation enters positively and significantly, while that on human capital is insignificant. As expected, the openness rate and FDI over GDP have positive effects, but with only the former being significant.

The remaining columns in Table 1 check that the impact of our key complexity indicator is robust to the inclusion of the control variables commonly used in the literature to account for an economy's productive structure. Column 3 introduces a measure of export diversification, the Theil index,[18] which is typically used to analyze the evolution of export-diversification patterns with economic development. In line with the existing literature (Cadot *et al.*, 2011; Imbs & Wacziarg, 2003), the Theil index enters with a negative sign, suggesting that diversification rises with economic growth in China. This coefficient is however insignificant and does not affect that on complexity. In column 4, we add the share of natural-resource exports over GDP, since we may worry that complexity is capturing the effect of intrinsically low-ubiquity natural-resource products. Natural-resource exports are identified using the classification in Sachs and Warner (1999). This variable enters with a positive but insignificant coefficient, while the impact of complexity remains unchanged. In column 5, we control for the contribution of both manufacturing and services to city GDP. We find a negative but marginally significant effect of the share of the secondary sector and an insignificant impact of the share of the tertiary sector. However, the coefficient on the complexity indicator is again unchanged. In column 6, we replace the openness ratio by the export rate, and in column 7 we control for population size. Neither of these variables significantly affects economic growth. Overall our results support those in Hidalgo and Hausmann (2009), in that regions tend to converge to the levels of income that correspond to their measured complexity.

Across the various specifications, the point estimate on complexity is stable at 0.007, significant at the 1% significance level. As our estimated coefficient is a semi-elasticity, we calculate that a one standard deviation increase in complexity increases the annual growth rate by 0.7 percentage points. This is a clearly economically-significant impact.

Table 1. *Within regressions (city): economic complexity and GDP per capita growth during 1997–2009 (3× 4-year sub-periods)*

Dependent variable	City yearly GDP per capita growth 1997–2009, (3× 4-year sub-periods)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Initial GDP per capita	−0.146***	−0.144***	−0.144***	−0.140***	−0.136***	−0.144***	−0.144***
	(0.012)	(0.012)	(0.012)	(0.013)	(0.014)	(0.012)	(0.012)
Export sophistication	0.015*	0.012					
	(0.008)	(0.007)					
Complexity		0.006***	0.007***	0.007***	0.007***	0.007***	0.007***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Investment rate	0.011**	0.012**	0.012**	0.011**	0.014***	0.012***	0.011**
	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)
Human capital	−0.001	−0.002	−0.002	−0.005	−0.001	−0.001	−0.002
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Openness rate	0.006	0.007*	0.007*	0.004	0.007**		0.006
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)		(0.004)
FDI rate	0.002	0.001	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Theil index			−0.003				
			(0.003)				
Nat. resource exports over GDP				0.004			
				(0.002)			
Secondary GDP share					−0.031*		
					(0.018)		
Tertiary GDP share					0.001		
					(0.020)		
Exports over GDP						0.003	
						(0.004)	
Population							−0.013
							(0.024)
Fixed effects	City fixed effects and year fixed effects						
Observations	623	623	623	623	623	623	623
R-squared	0.758	0.761	0.760	0.762	0.762	0.758	0.760
Number of cities	221	221	221	221	221	221	221

Notes: Heteroskedasticity–robust standard errors are shown in parentheses; standard errors are clustered at the city level; all variables are in logs, except for complexity and the Theil index.
* Significance at the 10% confidence level.
** Significance at the 5% confidence level.
*** Significance at the 1% confidence level.

(b) *Robustness checks*

Tables 2 and 3 contain further robustness checks. In Table 2 we verify that our findings are not driven by the way in which we define revealed comparative advantage to calculate complexity and by outliers. In Table 3 we rely on alternative estimation strategies to take potential endogeneity into account.

As in Eqn. (9), our complexity indicator reflects only products which are exported with Revealed Comparative Advantage (RCA). In this formula, only goods for which $M_{ck} = 1$ contribute to the complexity of city c. We should thus check that our results are not sensitive to the threshold used to measure RCAs. In column 1 of Table 2, we consider that location j has an RCA in product k when RCA_{jk}, as defined in Eqn. (4), is strictly greater than 2, instead of 1 as in our baseline specification. The results in column 2 use a criterion of $RCA > 1.5$. Neither of these changes has any impact on the results. In columns 3 and 5 we consider specific city features, and check that our results hold when removing locations that are known to be clearly different from others, in terms of location and policy particularities which have made them richer, faster-growing, more open, and more likely to export complex goods. In column 3, we estimate our model excluding the four cities with province status (Beijing, Tianjin, Shanghai, and Chongqing), which stand out for their greater political autonomy and smaller surface area. Our main result is robust to this exclusion. In column 4 we exclude the 53 cities with special policy zones from Wang and Wei (2010). These zones were created by the government, starting in 1979 in Guangdong, in order to promote industrial activity, innovation and exports.

They offer lower taxes and faster administrative procedures in order to favor industrial clustering. Despite the sharp reduction in the number of observations, the effect of complexity on GDP per capita growth is unaffected. We further check that the effect of complexity is not confined to cities with more exports and estimate, in column 5, our model without the top decile of exporting cities: our estimates are again virtually unchanged. In the remaining columns of Table 2, we exclude the top and bottom three cities according to different criteria from our sample to test if extreme values affect our results. In column 6 the criterion is the level of GDP, in column 7 growth performance, in column 8 complexity, and in column 9 openness. Our results seem robust to these exclusions and are thus not driven by extreme values in those key dimensions.

Table 3 considers alternative estimation techniques which take endogeneity and measurement issues into account. Column 1 shows the baseline results in which city complexity is computed using the time-invariant product-level. As discussed in Section 2, our product-complexity indicator (defined in Eqn. (5)) is calculated for 1997, the first year of our sample.

Table 2. *Robustness checks: complexity and GDP per capita growth*

Dependent variable	City yearly GDP per capita growth 1997–2009, (3× 4-year sub-periods)								
	(1)	(2)	(3) No. super 4 cities	(4) No. policy zone	(5) No. top 10% exporters	(6) W/o GDP extremes	(7) W/o growth extremes	(8) W/o complexity extremes	(9) W/o openness extremes
Initial GDP per capita	−0.144***	−0.143***	−0.142***	−0.147***	−0.144***	−0.143***	−0.156***	−0.143***	−0.144***
	(0.012)	(0.012)	(0.013)	(0.014)	(0.014)	(0.012)	(0.013)	(0.013)	(0.013)
Complexity			0.007***	0.007***	0.007***	0.007***	0.008***	0.008***	0.007***
			(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
Complexity (cut-off 2.0)	0.008***								
	(0.002)								
Complexity (cut-off 1.5)		0.007***							
		(0.002)							
Investment rate	0.012**	0.012**	0.011**	0.001	0.007	0.010**	0.009**	0.013***	0.010**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)
Human capital	−0.002	−0.002	−0.004	−0.006	−0.003	−0.001	−0.003	−0.002	0.001
	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.008)
Openness rate	0.007*	0.007*	0.007*	0.006	0.003	0.007*	0.006*	0.007*	0.007
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)
FDI rate	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Fixed effects	City fixed effects and year fixed effects								
Observations	623	623	611	466	569	606	605	605	605
R-squared	0.761	0.759	0.760	0.799	0.777	0.767	0.774	0.753	0.763
Number of cities	221	221	217	168	203	215	215	215	215

Notes: Heteroskedasticity–robust standard errors are shown in parentheses; standard errors are clustered at the city level; all of our variables are in logs, except for complexity and the Theil index; extremes correspond to the top and bottom three cities according to each criteria for 1997.
* Significance at the 10% confidence level.
** Significance at the 5% confidence level.
*** Significance at the 1% confidence level.

Table 3. *Alternative estimation methods: complexity and GDP per capita growth*

Dependent variable	City yearly GDP per capita growth				
	(1) Benchmark	(2) Time-variant $K_{k,15}$	(3) Long difference 1997–2009	(4) First difference	(5) System GMM
Initial GDP per capita	−0.143***	−0.144***	−0.003	−0.197***	−0.087***
	(0.012)	(0.012)	(0.004)	(0.014)	(0.016)
Complexity	0.007***	0.005**	0.004**	0.008***	0.018***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.005)
Investment rate	0.012**	0.012**	0.005	0.003	−0.005
	(0.005)	(0.005)	(0.004)	(0.004)	(0.008)
Human capital	−0.002	−0.001	−0.002	−0.001	−0.013
	(0.007)	(0.007)	(0.009)	(0.007)	(0.021)
Openness rate	0.007*	0.007*	0.002	0.010***	0.035***
	(0.004)	(0.004)	(0.002)	(0.004)	(0.008)
FDI rate	0.001	0.001	0.001	0.001	0.004
	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)
City fixed effects	Yes	Yes	No	Yes	Yes
Year fixed effects	Yes	Yes	No	Yes	Yes
Observations	623	623	184	400	623
R-squared	0.760	0.758	0.069	0.598	
Number of cities	221	221	184	219	221
Number of instruments					19
Hansen test					12.21
p-value					0.342
AR(1)					−2.89
p-value					0.004

Notes: GDP per capita growth is calculated for three 4-year sub-periods in all columns apart from column 3; heteroskedasticity–robust standard errors are in parentheses; standard errors are clustered at the city level; all variables are in logs, except for complexity and the Theil index.
* Significance at the 10% confidence level.
** Significance at the 5% confidence level.
*** Significance at the 1% confidence level.

In column 2 of Table 3 we instead use a year-specific product complexity measure, which does not change our results. In the remaining columns of Table 3 we depart from the fixed-effect model. As emphasized by Nickell (1981), the autoregressive parameter is likely downward biased as the introduction of the lagged dependent variable together with city fixed effects renders the OLS estimator biased and inconsistent. Two different strategies are then used to remove the individual time-invariant component. In column 3, our results are estimated using a long difference in per capita GDP growth on initial complexity during 1997–2009. In column 4, we use first differences instead of fixed effects. Despite the sharp decline in the number of observations, the results are virtually unchanged. Finally, in column 5 we address the issue of endogeneity. We estimate our model using the system-GMM estimator proposed by Arellano and Bover (1995) and Blundell and Bond (1998). We follow Roodman (2006) and use only two lags for the lagged dependent variable and one and two lags for the other (predetermined) variables. As suggested by Roodman (2006), the number of instruments, shown at the foot of the column is considerably below the number of groups present in our estimations.

The consistency of the GMM estimates depends on instrument validity. The Hansen test of overidentifying restrictions indicates that the orthogonality conditions cannot be rejected at the 10% level. We thus do not reject the null hypothesis that the instruments are appropriate. The strong link between complexity and growth does not appear to be driven by simultaneity bias.

(c) *Domestic embeddedness as a prerequisite*

Our results so far have confirmed, in the context of Chinese cities, the cross-country evidence that specialization in complex products is beneficial, in growth terms. This evidence however has not accounted for the huge heterogeneity in trade regimes and firm types that exists in Chinese exports. They also do not allow us to conclude whether the FDI- and processing trade-strategy in China was successful in boosting growth. Disentangling between the various sources of complexity is hence key for us to be able to conclude as to the capacity of FDI inflows and processing trade to produce the expected growth-enhancing quality upgrades to a country's product structure. Doing so furthermore allows us to see whether, as suggested in the literature, the positive growth externalities from complex exports are conditional on the trade regime. Jarreau and Poncet (2012) and Wang and Wei (2010) find no association between processing activities, on the one hand, and growth and sophistication, on the other. A similar lack of correlation is found in the case of foreign-firm export activities. These results suggest that the complexity associated with processing (foreign dominated) export activities may not produce any growth gains, as this does not reflect the characteristics of local production, but rather imported inputs. This is an important question, since China's trade patterns are greatly influenced by the presence of foreign companies and processing trade. For example, in 2007, 54% of Chinese exports were in the processing-trade sector.

Table 4. *Decomposition of the sources of complexity and growth*

Dependent variable	City yearly GDP per capita growth 1997–2009, (3× 4-year sub-periods)						
	(1) Domestic	(2) Foreign	(3) DOM-ordinary	(4) DOM-processing	(5) FOR-ordinary	(6) FOR-processing	(7) All four
Initial GDP per capita	−0.143***	−0.145***	−0.143***	−0.145***	−0.145***	−0.145***	−0.143***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Domestic complexity	0.007***						
	(0.003)						
Foreign complexity		0.002					
		(0.002)					
Complexity—domestic ordinary			0.006**				0.006**
			(0.002)				(0.003)
Complexity—domestic processing				−0.001			−0.001
				(0.002)			(0.002)
Complexity—foreign ordinary					0.002		0.002
					(0.002)		(0.002)
Complexity—foreign processing						0.001	−0.001
						(0.001)	(0.001)
Investment rate	0.012**	0.011**	0.012***	0.011**	0.012**	0.011**	0.012***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Human capital	−0.002	0.001	−0.001	0.001	0.001	0.001	−0.001
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Openness rate	0.007**	0.006	0.007*	0.006	0.006	0.006	0.007*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
FDI rate	0.001	0.002	0.001	0.002	0.002	0.002	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Fixed effects	City fixed effects and year fixed effects						
Observations	623	623	623	623	623	623	623
R-squared	0.760	0.756	0.759	0.755	0.756	0.755	0.760
Number of cities	221	221	221	221	221	221	221

Notes: Heteroskedasticity–robust standard errors are shown in parentheses; standard errors are clustered at the city level; all of our variables are in logs, except for the complexity measures.
* Significance at the 10% confidence level.
** Significance at the 5% confidence level.
*** Significance at the 1% confidence level.

Table 4 disentangles the roles of trade regime and firm type in the complexity-growth relationship. In columns 1 and 2, we introduce the complexity of a city's exports calculated only using data on domestic and foreign firms, respectively. In the first column, based on domestic firms' export baskets, complexity attracts a positive and significant coefficient, of the same size as previously. By way of contrast, when complexity is based on foreign firms it is insignificant. In the following four columns (3–6), complexity is split into its four components of processing and ordinary trade, separately for domestic and foreign entities. The correlation with subsequent economic growth is positive and significant only in column 3, where complexity is measured based on ordinary export activities undertaken by domestic firms. In column 7 we simultaneously include the four components: again, only the complexity associated with the ordinary export activities of domestic firms is positive and significant. The other three components seem to yield no direct growth gains. [19] Our results are in line with the finding in Jarreau and Poncet (2012) based on sophistication, and suggest that the upgrading-growth relationship pertains exclusively to the capabilities of firms which are well-embedded in the local economy.

Our results hold in the various robustness checks carried out above with the aggregate complexity measure in Tables 1–3. Tables 5–7 in the appendix check that our results hold when we add various control variables, remove outliers, and adopt different estimation approaches. We consistently find that the positive and significant association between complexity and subsequent economic growth is limited to the ordinary export activities undertaken by domestic firms: no direct gains result from either processing trade activities or foreign firms. [20]

We interpret our results as indicating that domestic embeddedness is crucial for capacity building and technology adoption to be growth-enhancing and that in the context of China, these conditions are not met for the diffusion of technology incorporated in assembly activities. This may be related to the "enclave" approach to internationalization adopted by Chinese authorities, confining foreign investment and processing activities to special economic zones dedicated to export development. This strategy may have limited the local embeddedness of the capacities deployed by foreign entities, and hampered the emergence of the expected growth gains from their activities.

There may be additional impeding factors in China explaining why complexity affects growth only when it corresponds to the capabilities truly embedded in the local economy. For example, potential technological spillovers may be hampered by limited domestic absorption capacity or the absence of substantial and well-directed technological efforts by foreign and domestic firms (Crespo & Fontoura, 2007). The empirical results in Li (2011) on the complementarity between in-house and imported technology are consistent with this argument. Li shows that importing foreign technology alone does not facilitate innovation in Chinese state-owned high-tech enterprises unless in-house R&D is also carried out. He also finds that firms have less difficulty in absorbing domestic technological knowledge than in utilizing foreign technology, which is consistent with our claim that the benefits from upgrading are contingent on the source of external knowledge.

4. CONCLUSION

We here confirm the specificity of the upgrading-growth relationship, appealing to regional variation within one country (China) over the 1997–2009 period using the new indicator of complexity of Hidalgo and Hausmann (2009). Our results confirm the stylized fact in cross-country regressions that regions specializing in more complex goods subsequently grow faster, controlling for the level of income. They however underline that the sources of product upgrading matter, and that domestic embeddedness is key for capacity building and technology adoption to be growth enhancing. Growth benefits pertain exclusively to the capabilities of domestic firms engaged in ordinary trade, and no direct gains emanate from the complexity of goods produced by either processing trade activities or foreign firms. Our findings cast doubt on the capacity of China (as well as developing countries in general) to successfully build up their own growth-enhancing capabilities via technology acquisition from assembling activities and foreign investment.

NOTES

1. A related paper is Kali, Reyes, McGee, and Shirrell (2013) which focuses on a complementary growth mechanism based on synergies between the products in a country's export basket. It suggests that greater synergies among the current set of products improve the capacity of a country to move to higher income products and experience higher growth rates.

2. For a review of the research documenting the superior performance of foreign affiliates see Arnold and Javorcik (2009).

3. Firms can engage in both processing and ordinary trade activities simultaneously. Using Chinese customs data for 2006, we compute that roughly 20% of firms operate in both trade sectors. The share is 30.5% for foreign firms and 11.9% for domestic firms, respectively.

4. Harding and Javorcik (2012) reach a similar conclusion at the worldwide level: FDI does not seem to increase the similarity of export structure between developing and developed countries.

5. Dai *et al.* (2011) find that processing trade involves unskilled labor-intensive jobs with low profitability and produces low-quality goods.

6. Lall (2000) proposes a classification of products by technological level, but at the relatively aggregated 3-digit SITC level.

7. A very similar measure of product sophistication is developed by Lall, Weiss, and Zhang (2006).

8. Hidalgo and Hausmann (2009) use Lego models as an analogy. Lego pieces are held to represent the capabilities available across the world, while Lego models correspond to the different products and Lego buckets represent countries. Complex Lego models (products) are those using Lego pieces (capabilities) that are rare, so that they are likely to be found in only few Lego buckets (countries) and especially in those that have both many and rare Lego pieces.

9. We consider, following Hidalgo and Hausmann (2009), that a country j has a revealed comparative advantage in a product k if $RCA > 1$. In robustness checks we show that our results continue to hold if we use 1.5 or 2 as alternative thresholds.

10. Hidalgo and Hausmann (2009) find the stylized fact that more developed countries are also those who have a higher level of diversity. This is consistent with the expectation that diversity reflects the multiplicity of capabilities (technology, labor skills, institutions, inputs, *etc.*) required to produce different products.

11. See Felipe *et al.* (2012) for an extensive presentation of the product and country complexity measures and a discussion of the product and country rankings.

12. This dataset is constructed based on COMTRADE data using an original procedure that reconciles the declarations of exporters and importers (Gaulier & Zignago, 2010). The harmonization procedure enables the number of countries for which trade data are available to be extended considerably, as compared to the original dataset. This uses the 1992 product nomenclature. BACI is downloadable from http://www.cepii.fr/anglaisgraph/bdd/baci.htm.

13. Chinese customs data are reported using an 8-digit classification. We convert these into the 1992 Harmonized System (HS) classification to match the 1992 classification used in the BACI dataset.

14. This definition is provided in "Measures of the Customs of the People's Republic of China on the Control of Processing-Trade Goods" released in 2004 (Manova & Yu, 2012).

15. Our sample includes 221 cities. This number corresponds to the cities for which we have consistent information both on trade flows and macro-level determinants such as GDP and population.

16. The standard deviation is computed yearly as $\sigma_{K_c^t} = \sqrt{\frac{\sum_c (K_c^t)^2}{n} - \left(\frac{\sum_c K_c^t}{n}\right)^2}$.

17. The first-difference estimator is obtained by running a pooled OLS estimation on Eqn. (11) transformed into first difference. The GMM system estimator for dynamic panel data models combines equations in first difference and in level with an instrumental strategy proposed by Blundell and Bond (1998). Lagged differences and lagged levels of the variables are used as instruments for the endogenous levels and differences respectively.

18. For each city and year we compute $Theil = \frac{1}{n}\sum_{k=1}^{n} \frac{x_k}{\mu} ln\left(\frac{x_k}{\mu}\right)$, where $\mu = \frac{1}{n}\sum_{k=1}^{n} x_k$, x_k denotes the exports of good k and n is the number of exported goods. The negative sign is expected as an increase in the Theil index reflects less diversification (Cadot, Carrère, & Strauss-Kahn, 2011).

19. In unreported robustness checks available upon request we verify that our results remain when we control for what the city export growth would have been over the period had the city maintained its world market share of the goods it was exporting in the initial year. Our findings are also confirmed when we include what Hausmann *et al.* (2011) call opportunity value which measures how well poised cities are for structural transformation in terms of their position in the product space. Our main message is furthermore robust when controlling for the growth of exports.

20. In unreported robustness checks we verify that the lack of significance for the processing complexity measure does not simply reflect the fact that processing (foreign-dominated) exports are a less good measure of a location's production capabilities. We recomputed our complexity indicators using domestic value-added content of the exports instead of the total exports. We borrowed the sector-level ratios of domestic value added from Koopman, Wang, and Wei (2008) and used the concordance table between sectors and HS6 products from Upward, Zheng, and Wang (2013). When re-estimating the specifications in Table 4 using the modified complexity (measured based solely domestic value-added content), we obtain similar results: significant coefficients are found solely for domestic complexity and domestic ordinary complexity.

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APPENDIX A

See Tables 5–10.

Table 5. *Robustness checks (additional controls): complexity components and GDP per capita growth*

Dependent variable	City GDP per capita growth 1997–2009, (3× 4-year sub-periods)				
	(1)	(2)	(3)	(4)	(5)
Initial GDP per capita	−0.144***	−0.140***	−0.137***	−0.144***	−0.144***
	(0.012)	(0.012)	(0.014)	(0.012)	(0.012)
Complexity—domestic ordinary	0.006**	0.006**	0.006**	0.006**	0.006**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Complexity—domestic processing	−0.001	−0.001	−0.001	−0.001	−0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Complexity—foreign ordinary	0.002	0.002	0.001	0.001	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Complexity—foreign processing	−0.001	−0.001	−0.001	−0.001	−0.001
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)
Investment rate	0.012***	0.012***	0.014***	0.013***	0.012***
	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)
Human capital	0.001	−0.003	0.001	0.001	−0.001
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Openness rate	0.007**	0.004	0.008**		0.007*
	(0.004)	(0.004)	(0.004)		(0.004)
FDI rate	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Theil index	−0.004				
	(0.003)				
Nat. resource exports		0.004*			
		(0.002)			
Secondary share			−0.032*		
			(0.018)		
Tertiary share			−0.003		
			(0.020)		
Exports over GDP				0.005	
				(0.003)	
Population					−0.010
					(0.025)

Table 5 (*continued*)

Fixed effects	City fixed effects and year fixed effects				
Observations	623	623	623	623	623
R-squared	0.761	0.763	0.762	0.758	0.760
Number of cities	221	221	221	221	221

Notes: Heteroskedasticity–robust standard errors are shown in parentheses; standard errors are clustered at the city level; all of our variables are in logs, except for the complexity measures and the Theil index.
* Significance at the 10% confidence level.
** Significance at the 5% confidence level.
*** Significance at the 1% confidence level.

Table 6. *Robustness checks (outliers): complexity components and GDP per capita growth*

Dependent variable	City GDP per capita growth 1997–2009, (3× 4-year sub-periods)								
	(1)	(2)	(3) No. super 4 cities	(4) No. policy zone	(5) No. top 10% exporters	(6) W/o GDP extremes	(7) W/o growth extremes	(8) W/o complexity extremes	(9) W/o openness extremes
Initial GDP per capita	−0.144***	−0.144***	−0.142***	−0.148***	−0.145***	−0.143***	−0.155***	−0.143***	−0.144***
	(0.012)	(0.012)	(0.012)	(0.014)	(0.013)	(0.012)	(0.013)	(0.013)	(0.012)
Complexity—domestic ordinary	0.006**	0.006**	0.006**	0.007***	0.005**	0.006**	0.006**	0.006**	0.006**
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
Complexity—domestic processing	−0.001	−0.001	−0.001	−0.001	−0.002	−0.001	−0.001	−0.001	−0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Complexity—foreign ordinary	0.001	0.002	0.002	0.001	0.002	0.002	0.002	0.001	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Complexity—foreign processing	−0.002	−0.001	0.001	−0.001	−0.001	−0.001	−0.001	0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Investment rate	0.012***	0.012***	0.011**	0.001	0.008	0.010**	0.010**	0.013***	0.010**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)
Human capital	−0.001	−0.001	−0.002	−0.004	−0.001	0.001	−0.001	−0.001	0.003
	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.007)	(0.006)	(0.007)	(0.007)
Openness rate	0.007*	0.007*	0.007**	0.007*	0.003	0.007*	0.006*	0.007*	0.007
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)
FDI rate	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Fixed effects	City fixed effects and year fixed effects								
Observations	623	623	611	466	569	606	605	605	605
R-squared	0.760	0.759	0.760	0.800	0.777	0.767	0.773	0.752	0.763
Number of cities	221	221	217	168	203	215	215	215	215

Notes: Heteroskedasticity–robust standard errors are shown in parentheses; standard errors are clustered at the city level; all of our variables are in logs, except for the complexity measures; extremes correspond to the top and bottom three cities according to each criteria in 1997.
* Significance at the 10% confidence level.
** Significance at the 5% confidence level.
*** Significance at the 1% confidence level.

Table 7. *Alternative estimation methods: complexity components and GDP per capita growth*

Dependent variable	Average GDP per capita growth for each period				
	(1) Benchmark	(2) Yearly $K_{k,15}$	(3) Long cross section	(4) First-diff	(5) System-GMM
Initial GDP per capita	−0.143***	−0.144***	−0.004	−0.198***	−0.101***
	(0.012)	(0.012)	(0.004)	(0.014)	(0.019)
Complexity domestic ordinary	0.006**	0.004**	0.006**	0.006**	0.010**
	(0.003)	(0.002)	(0.003)	(0.003)	(0.005)
Complexity domestic processing	−0.001	−0.002	−0.002	−0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Complexity foreign ordinary	0.002	0.001	0.003	0.002	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)
Complexity foreign processing	−0.001	−0.001	−0.004**	−0.001	0.005
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)
Investment rate	0.012***	0.012***	0.007*	0.003	−0.010
	(0.005)	(0.005)	(0.004)	(0.004)	(0.008)
Human capital	−0.001	0.001	−0.001	0.001	−0.024
	(0.007)	(0.007)	(0.009)	(0.007)	(0.017)
Openness rate	0.007*	0.007*	0.002	0.010***	0.038***
	(0.004)	(0.004)	(0.002)	(0.004)	(0.008)
FDI rate	0.001	0.001	0.001	0.001	0.004
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)
City fixed effects	Yes	Yes	No	Yes	Yes
Year fixed effects	Yes	Yes	No	Yes	Yes
Observations	623	623	184	400	623
R-squared	0.760	0.758	0.112	0.597	
Number of cities	221	221		219	221
Number of instruments					28
Hansen test					20.55
p-value					0.196
AR(1)					−2.42
p-value					0.016

Notes: Heteroskedasticity–robust standard errors are shown in parentheses; standard errors are clustered at the city level; all of our variables are in logs, except for the complexity measures.
* Significance at the 10% confidence level.
** Significance at the 5% confidence level.
*** Significance at the 1% confidence level.

Table 8. *City list by province*

Province name	City name
Anhui	Anqing, Bengbu, Chaohu, Chizhou, Fuyang, Hefei, Huaibei, Huainan, Huangshan Liuan, Maanshan, Tongling, Wuhu, Xuancheng
Beijing	Beijing
Chongqing	Chongqing
Fujian	Fuzhou, Longyan, Nanping, Ningde, Putian, Quanzhou, Sanming, Xiamen, Zhangzhou
Gansu	Baiyin, Lanzhou, Tianshui
Guangdong	Chaozhou, Foshan, Guangzhou, Heyuan, Huizhou, Jiangmen Jieyang, Maoming, Meizhou, Shantou, Shanwei, Shaoguan, Shenzhen Yangjiang, Zhanjiang, Zhongshan, Zhuhai
Guangxi	Beihai, Guilin, Qinzhou, Yulin
Guizhou	Guiyang, Liupanshui, Zunyi
Hebei	Baoding, Cangzhou, Chengde, Handan, Hengshui, Langfang, Qinhuangdao Shijiazhuang, Tangshan, Xingtai, Zhangjiakou
Heilongjiang	Daqing, Harbin, Hegang, Heihe, Jiamusi, Jixi, Mudanjiang, Qiqihar Qitaihe , Shuangyashan, Suihua
Henan	Anyang, Hebi, Jiaozuo, Kaifeng, Luohe, Luoyang, Nanyang, Puyang, Sanmenxia Shangqiu, Xinxiang, Xinyang, Xuchang, Zhengzhou, Zhoukou, Zhumadian
Hubei	Ezhou, Huanggang, Huangshi, Jingmen, Jingzhou, Shiyan, Suizhou, Wuhan

Table 8 (*continued*)

Province name	City name
	Xiangfan, Xianning, Xiaogan, Yichang
Hunan	Changde, Changsha, Chenzhou, Hengyang, Huaihua, Loudi, Shaoyang, Xiangtan Yiyang, Yueyang, Zhuzhou
Inner Mongolia	Baotou, Chifeng, Hulunbeir, Wuhai
Jiangsu	Changzhou, Huaian, Lianyungang, Nanjing, Nantong, Suqian, Suzhou, Taizhou Wuxi, Xuzhou, Yancheng, Yangzhou, Zhenjiang
Jiangxi	Fuzhou, Ganzhou, Jian, Jingdezhen, Jiujiang, Nanchang, Pingxiang Shangrao, Xinyu, Yichun, Yingtan
Jilin	Changchun, Jilin, Siping, Tonghua
Liaoning	Anshan, Benxi, Dalian, Dandong, Fushun, Fuxin, Jinzhou, Liaoyang, Panjin Shenyang, Tieling, Yingkou
Ningxia	Yinchuan
Shaanxi	Ankang, Baoji, Tongchuan, Weinan, Xian, Xianyang, Yulin
Shandong	Dezhou, Dongying, Heze, Jinan, Jining, Laiwu, Liaocheng, Linyi, Qingdao Rizhao, Taian, Weifang, Weihai, Yantai, Zibo
Shanghai	Shanghai
Shanxi	Changzhi, Datong, Jincheng, Jinzhong, Linfen, Taiyuan, Xinzhou, Yangquan Yuncheng
Sichuan	Chengdu, Deyang, Guangan, Guangyuan, Leshan, Luzhou, Mianyang, Nanchong Neijiang, Panzhihua, Suining, Yaan, Yibin, Zigong
Tianjin	Tianjin
Xinjiang	Urumqi
Yunnan	Baoshan, Kunming, Qujing, Yuxi, Zhaotong
Zhejiang	Hangzhou, Huzhou, Jiaxing, Jinhua, Lishui, Ningbo, Quzhou, Shaoxing Wenzhou, Zhoushan

Table 9. *Summary statistics. No. of observations = 623*

Variable	Mean	Std. Dev.	Min.	Max.
Av. yearly GDP per cap. growth (1997–2009)	0.11	0.05	−0.10	0.34
GDP per capita (yuan)	12,550	16,323	1880	272,132
Complexity	0	0.99	−2.87	3.36
Complexity dom. ODT	0	1	−3.10	5.42
Complexity dom. PCS	0	1	−3.58	4.15
Complexity for. ODT	0	1	−3.31	4.52
Complexity for. PCS	0	1	−2.9	4.22
Export sophistication ($)	10947.2	2452.10	539.75	19687.4
Investment rate	0.31	0.14	0.05	0.83
Human capital	0.06	0.01	0.01	0.13
Openness rate	0.02	0.04	0	0.38
FDI rate	55.12	79.77	0.02	681.03
Theil	4.98	1.29	2.05	8.33
Natural resource exp. over GDP	0.002	0.004	0	0.03
Secondary GDP share	0.45	0.10	0.15	0.88
Tertiary GDP share	0.35	0.07	0.09	0.68
Exports over GDP	0.01	0.02	0	0.21
Population (thousands)	4468	3074	406	31,692

Table 10. *Pairwise correlations*

								Complexity components			
	Growth	GDP pc	Complexity	Inv. rate	Hum. Cap.	Open	FDI	Dom. ODT	Dom. PCS	For. ODT	For. PCS
GDP per cap growth	1										
GDP per capita	0.314*	1									
Complexity	0.208*	0.0145	1								
Investment rate	0.257*	0.327*	0.189*	1							
Human capital	0.0823	0.224*	−0.221*	−0.0732	1						
Openness rate	0.340*	0.648*	−0.1044	0.253*	0.259*	1					
FDI rate	0.256*	0.416*	−0.0549	0.1255	0.238*	0.582*	1				
Complexity dom. ODT	0.208*	0.0212	0.875*	0.147*	−0.198*	−0.1152	0.0249	1			
Complexity dom. PCS	0.1207	−0.0364	0.570*	0.1082	−0.0355	−0.0494	−0.0319	0.533*	1		
Complexity for. ODT	0.1180	0.0382	0.451*	0.0661	−0.0958	−0.0947	−0.0793	0.280*	0.195*	1	
Complexity for. PCS	0.0015	−0.0672	0.414*	0.248*	−0.162*	−0.182*	−0.169*	0.240*	0.206*	0.414*	1

Notes: Calculated for 1997; see the text for variable definitions.
* Significance at the 0.05 level.