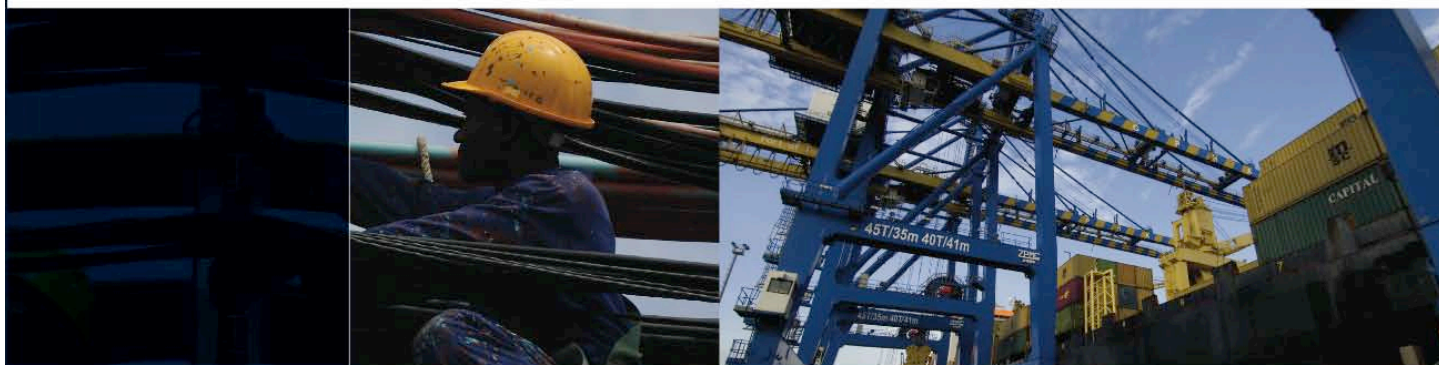


LEARNING TO COMPETE

Working Paper No. 3



Measuring Industry Agglomeration and Identifying the Driving Forces

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Abstract

Understanding industry agglomeration and its driving forces is critical for the formulation of industrial policy in developing countries. Crucial to this process is the definition and measurement of agglomeration. We propose a new measure and examine what it reveals about the importance of transport costs, labour market pooling, and technology transfer for agglomeration processes. We contrast this analysis with insights from existing measures in the literature and find very different underlying stories at work. An exceptionally rich set of data from Vietnam makes us confident that our measure is superior at least in developing country contexts.

Keywords: Industry agglomeration, technology spillovers, labour market pooling, Vietnam
JEL classification: L14, L60, O14, O33

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Learning to Compete (L2C) is a collaborative research program of the Africa Growth Initiative at Brookings (AGI), the African Development Bank, (AfDB), and the United Nations University World Institute for Development Economics Research (UNU-WIDER) on industrial development in Africa. Outputs in this Working Paper Series have been supported by all three institutions.

AGI-Brookings is grateful for the contribution of an anonymous donor for funding its work under the collaborative research program.

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1 Introduction

The geographic clustering of manufacturing activity has long been recognized as an important mechanism for facilitating industrial growth in both developed and developing countries (Krugman 1991; Markusen and Venables 1999). Also more recent contributions speak to the issue. Deichmann et al. (2008) use microdata for India and Indonesia and find that agglomeration benefits outweigh the costs of congestion and higher wages in clusters. Collier and Page (2009) examine case studies of firms in Chile, China, and Malaysia and find anecdotal support for positive agglomeration externalities in the form of knowledge transfers, productivity gains, and the development of a thick labour market. Bigsten et al. (2011) investigate the effects of clustering on firm performance and find that all else being equal, Ethiopian manufacturing firms located in clusters have higher productivity.

Although an extensive literature exists on the benefits to firms in clusters from agglomeration externalities, there is little empirical evidence, particularly in developing country contexts, as to which agglomerative forces are at work within a country and their relative importance. Identifying the driving forces of agglomeration is critical for governments in the formulation of industrial policy.¹ Three well-established theoretical reasons for firm clustering exist over and above that which can be explained by natural advantages.² First, the clustering of economic activity reduces transport costs and so firms along the supply chain have more incentive to locate near each other.³ Second, where industry is concentrated a large pool of labour will emerge facilitating better matching of workers to employers.⁴ Third, information and technology spillovers are more likely when firms are clustered (Marshall 1920; Krugman 1991; Fujita et al. 1999). Ellison et al. (2010) test these theories in the case of manufacturing firms in the USA and set a new and welcome standard for empirical testing of agglomerative forces. They use a measure of coagglomeration proposed by Ellison and Glaeser (1999) (EG) that is closely related to the covariance in employment shares between two industries within defined geographical regions.

In this paper, we aim to advance the literature by first proposing a different measure of agglomeration based on the physical location of firms. This is, in our assessment, a more appropriate measure of coagglomeration in developing country contexts. Like Ellison et al. (2010) we focus on agglomeration across sub-sectors or coagglomeration. Agglomerative forces between firms in the same sub-sector of course may also exist but we do not consider these in this paper. We exploit the fact that we have an exceptional set of data sources for manufacturing firms in Vietnam. Second, we also consider an absolute measure of coagglomeration where clusters are measured in terms of absolute size. Third, our data allow us to test the impact of transport costs, labour pooling, and technology spillovers on the clustering of firm activity along the lines of Ellison et al. (2010). Fourth, we are able to capture informal channels of technology diffusion between firms which adds an important

¹ See Pack and Saggi (2006) for a full discussion of industrial policy in developing countries.

² For evidence on the importance of exogenous natural advantages in determining the initial spatial pattern of enterprise location see Ellison and Glaeser (1999), Burchfield et al. (2006), and Bleakley and Lin (2012).

³ As highlighted by Krugman and Venables (1995) it could also be the case that as transport costs decline firms may have an incentive to locate away from their suppliers and markets where real wages are low due to low labour demand. As such the extent to which transport costs matter for the location choice of firms is an empirical question.

⁴ See Helsley and Strange (1990). Another interpretation is that there is a risk-sharing aspect to a large pool of labour and therefore labour market pooling makes workers and firms better off when firms face idiosyncratic demand shocks ([Krugman 1991](#); Overman and Puga 2010).

dimension to existing studies that have so far focused on formal or contracted technology transfers (Jaffe 1986; Ellison et al. 2010). Fifth, our analysis addresses whether agglomerative forces are different for high-tech and low-tech sectors. Sixth and finally, we perform the analysis at three levels of spatial disaggregation (commune, district, and province).

Our key result is that the two most important forces behind agglomeration are technology transfers and skills correlations. The magnitude of the effect of technology transfers would appear to be twice as large in Vietnam as that found by Ellison et al. (2010) for the USA. Moreover, we find that technology transfers occur primarily between high-tech firms but also between high-tech and low-tech firms within clusters. Importantly, when the analysis is repeated using the EG measure of coagglomeration, technology spillovers have an almost negligible role to play. This highlights that appropriate measurement is critical to the empirical testing of agglomeration.

Turning to skills correlations, our results capture both competition for labour and labour pooling which impact on agglomeration in opposite directions.⁵ It emerges that competition for unskilled labour acts as a negative agglomerative force while the pooling of skilled labour contributes to agglomeration through the clustering of high-tech firms. In contrast, when we use the EG measure of agglomeration, skills correlations are a positive agglomerative force for all firms. This reflects the different way in which the agglomeration measures are defined in this paper as compared with the EG measure used in Ellison et al. (2010).

We also amend our coagglomeration measure to consider *absolute* agglomeration between sectors. When we repeat the analysis using this alternative measure, in contrast to our results using the relative measure, we find natural cost advantages are the most important agglomerative force at all three levels of measurement. This is as expected when clusters are measured in terms of absolute size. The significance and relative importance of the other three agglomerative forces are consistent with the results using our relative measure.

The remainder of the paper is organized as follows. In section 2 we present our measure of coagglomeration and provide evidence on the extent of coagglomeration of industry pairings in Vietnam. Section 3 describes each of the agglomerative forces considered and presents the measures used in our analysis. Section 4 presents and discusses the results and section 5 concludes the paper.

2 Definition and measurement of agglomeration

In spite of the importance attached to agglomeration as a force in economic transformation and development, few attempts have been made in the empirical literature to explicitly define and measure the extent of clustering within countries.⁶ A notable exception is the Ellison and Glaeser (1997) EG index adapted by Ellison et al. (2010) to measure the extent of coagglomeration of two sectors. They use this as the dependent variable in their study of the impact of transport costs, labour correlations, and technology spillovers on coagglomeration.

⁵ Combes and Duranton (2006) argue that when firms employ workers from the same local labour market they face a tradeoff between the benefits of labour pooling and the costs of labour poaching.

⁶ Uchida and Nelson (2010) propose a country level agglomeration index that can be used by compare the extent of agglomeration across countries. This measure is also used by Felkner and Townsend (2011) in describing the spatial distribution of firms in Thailand. It does not capture, however, the extent to which firms in different sectors cluster together and cannot be used to analyse within-country variation in clustering, which is the aim of this paper.

Specifically, the EG coagglomeration index for two industries A and B is given by equation (1).

$$\gamma_{AB}^C = \frac{\sum_{m=1}^M (s_{mA} - x_m)(s_{mB} - x_m)}{1 - \sum_{m=1}^M x_m^2} \quad (1)$$

where m indexes administrative areas; s_{mA} is the share of industry A 's employment in area m ; s_{mB} is the share of industry B 's employment in area m ; and x_m is the mean employment share in the area m across all industries.

The EG measure is derived on the basis of the assumption that agglomeration is a result of a sequence of profit maximizing location decisions by individual firms. We note that this index is closely related to the covariance of the area-industry employment shares in the two industries. The EG index for two sectors A and B depends not only on the distribution of employment in industries A and B but also on the distribution of employment in all other sectors. This means that even if all firms in sector A and all firms in sector B are located in the same area, the EG index will not necessarily equal 1, even though the sectors are completely coagglomerated.⁷ The index therefore captures correlations in the relative size of the two sectors, in terms of employment shares in each area, compared with the relative size of all other sectors in all other areas.

Measuring coagglomeration in this way potentially overlooks an important channel for technology transfer in empirical analysis. Where high-tech firms are small in terms of number of employees the EG index may fail to identify the relative importance of high-tech clusters. To illustrate, we consider two high-tech clusters of sectors A and B of the same size located in different regions. Both consist of many small firms but in one region they account for a small proportion of overall employment while in another they account for a large proportion of overall employment. In the former case, the relative importance of the high-tech cluster will be less than in the latter on the basis of the EG measure.

Moreover, as the EG measure for two sectors is closely related to the covariance of the area-industry employment shares, it will also be closely related to the correlation in employment patterns for the two sectors. Therefore high skills correlations will be associated with large values of the EG index and skills correlations are likely to emerge in the econometric analysis as a positive force. Consequently empirical analysis using the EG index as a measure of coagglomeration may fail to capture competition for workers between sectors.

We believe both of these aspects are critical in developing country contexts. When agglomeration is thought of as the clustering of firms regardless of their size there is room for further development of the agglomeration measure. We therefore propose a measure of coagglomeration for use as the dependent variable that is based on the physical location of firms. Accordingly, for every possible set of two sectors A and B we calculate a colocation index which measures the extent to which they are located in the same area.⁸ We calculate this measure at the three different levels (or areas); commune, district, and province. More precisely, for m firms in sector A and n firms in sector B we take each firm i in sector A and

⁷ In the case where all sector pairs are fully clustered in different areas the EG measure will take a value of 1.

⁸ Ellison et al. (2010) also consider the exact location of firms in an alternative measure of coagglomeration based on Duranton and Overman's (DO) (2005) index. They find similar results to the EG measure. The DO index requires the Euclidean distance between sets of firms and our data are not detailed enough to compute this. However, we would expect that in a developing country context the results using the two different measures would not necessarily be similar for reasons we explore in this paper.

sum the number of firms in sector B that are located in the same area. We then take the number of colocated pairings as a proportion of all possible pairings across the two sectors (i.e., $m \times n$). This measure will be bound by 0 and 1. The colocation formula is given by equation (2).

$$colocation_{AB} = \frac{\sum_{i=1}^m \sum_{j=1}^n C_{ij}}{m \times n} \quad (2)$$

where $C_{ij} = 1$ if firms i and j are located in the same area, and 0 otherwise.

We also consider an absolute colocation measure given by equation (3).

$$AbsoluteColocation_{AB} = \sum_{i=1}^m \sum_{j=1}^n C_{ij} \quad (3)$$

where $C_{ij} = 1$ if firms i and j are location in the same area and 0 otherwise. This formula simply counts the number of firms in sector A that are located in the same area as firms in sector B . As this measure does not control for the total number of firms in sectors A and B it is a measure of absolute coagglomeration. It will therefore take on larger values for larger sectors.

Accordingly, we compute pairwise colocation measures for 43 manufacturing industries in Vietnam using the Enterprise Survey for 2007 provided by the General Statistics Office.⁹ The dataset includes all registered manufacturing enterprises at the end of the year with more than 30 employees, plus a random sample of 15 per cent of small registered enterprises with less than 30 employees. Along with the standard financial information the data also include the name of the commune that each firm is located in. There are three levels of administrative areas in Vietnam: communes, districts, and provinces. In 2007 there were 10,995 communes, 749 districts, and 67 provinces.

Table 1 presents the top ten colocation pairings for the manufacturing sector in Vietnam for each of the different regions. While there are differences in the important pairwise colocation patterns depending on whether the indices are constructed at the commune, district, or provincial level, some distinct patterns emerge. The main sectors that are likely to be coagglomerated with other sectors are the manufacture of various types of machinery. For example, a high level of coagglomeration is found between the manufacture of electrical machinery and the manufacture of precision and optical equipment, sectors where two-way technology spillovers are likely. Similarly, we find a high degree of coagglomeration between chemical products and processed rubber and by-products which may also use common technologies and so potentially may benefit from spillovers. We also find coagglomeration along the value chain. For example, firms manufacturing leather goods, plastics and ready-made apparel are likely to be colocated with firms manufacturing domestic appliances, suggesting that transport costs of inputs from the former upstream sectors to the latter downstream sector may be a motivating factor. Similarly, the printing and publishing sector is likely to be colocated with sectors that are likely to require information booklets including regulations or instructions for the products that they produce, for example the manufacture of medical and surgical equipment or the manufacture of precision and optical equipment.

⁹ The full list of sectors considered are listed in the Appendix. It should be noted that while it is possible using our data to construct coagglomeration indices for 4-digit [International Standard Industrial Classification](#) (ISIC) sector pairings we are constrained by the level of sector disaggregation available for the other variables used in our analysis. For this reason we must aggregate the 4-digit industry codes into a common set of sector codes that are available for all measures.

Table 1 also reveals some pairings that are less obvious, such as the high level of coagglomeration between the manufacture of milk and dairy products and the manufacture of machinery used for broadcasting, telecommunications, and information. This suggests that in at least some cases natural advantages also play a role in firms' location decisions. Table 2 presents the Top Ten coagglomeration pairs on the basis of the EG measure. Although there are some distinct differences between the pairings depending on the geographical area chosen, some clear patterns emerge. In particular, three sector pairings are highly coagglomerated at all three levels of measurement; electrical machinery and precision and optical equipment; production, processing, and preserving of meat and meat products and the manufacture of milk and dairy products; and the manufacture of milk and dairy products and publishing. The most notable difference between the two tables is that the Top Ten pairings based on the EG index contain far fewer high-tech sectors than the top pairings based on the colocation index.¹⁰ This supports our contention that the EG index may fail to identify the relative importance of high-tech clusters, particularly where high-tech sectors employ fewer workers. Although there are clear differences between the most coagglomerated pairings identified by each measure there is also some overlap; for example both measures reveal a high level of coagglomeration between the manufacture of electrical machinery and the manufacture of precision and optical equipment. Manufacture of electrical machinery and of precision and optical equipment are both high-tech sectors and they are large in terms of employment shares. In one district they account for the third and second highest employment shares respectively, over all sectors and over all districts. For this reason both the EG index and the colocation index identify these sectors as being highly coagglomerated.

3 Determinants of agglomeration

In this section we describe how we construct measures of each of the three drivers of agglomeration and the data sources used. In addition, we describe how we control for natural advantages in our empirical analysis.

3.1 Transport costs

Firms wish to minimize their costs in order to maximize profits. Transportation of goods, both to customers and from suppliers, is more expensive the further the goods need to be transported. Therefore firms will have an incentive to locate near to their suppliers and/or their customers in order to reduce costs. To capture the extent to which transport costs matter in the location decisions of firms we use the input-output linkages between different industrial sectors. Following the approach of Ellison et al. (2010) we use the Vietnam Supply and Use tables (SUT) for 2007.

The SUT provides information on the use of 138 commodities in 112 production activities. Commodities and production activities are mapped to the 4-digit ISIC codes used in the Vietnamese Enterprise Survey and 43 manufacturing industry codes that are comparable across the two datasets are generated. Details of these codes are provided in the Appendix. The information in the SUT is aggregated to the new industry codes. We consider three different measures of input-output linkages as in Ellison et al. (2010). First, we consider the

¹⁰ Sectors 1–22 inclusive, plus sector 43, are defined as low-tech.

flow of inputs between each industry pairing. We compute the proportion of total inputs that sector A buys from sector B and vice versa and take the maximum as a measure of the degree of input linkages between the two sectors. Second, we consider the proportion of total output that sector A provides to sector B and vice versa and take the maximum as a measure of the degree of output linkages between the two sectors. Third, we take the maximum of the input and output measures to produce the variable $InputOutput_{AB}$. Finally, we also take the maximum of the input and output measures in absolute terms, measured as the maximum of the total value of inputs/outputs that A sells/buys from B and vice versa. We expect that firms that are highly linked on the basis of this measure will be more likely to cluster.

3.2 Labour market pooling

To assess the importance of labour market pooling we examine the correlation in the types of occupations of workers employed in each of the different sectors. We use the Vietnam Household Living Standards Survey (VHLSS) for 2006 which is a representative sample of all households in Vietnam. The database contains information on the occupation of household members together with the 2-digit sector in which they are employed. These different occupation groups represent different skills sets that employers require from their workers. There are 32 different occupation groups specified. In order to measure the extent to which two different sectors employ workers with similar skills sets, and therefore have incentives to locate near a common ‘pooled’ labour market, we calculate the correlations between the employment patterns of all sets of two sectors. First, we calculate the share of each sector’s employment in each occupation (o) $Share_{AO}$. We then calculate the correlation between $Share_{AO}$ and $Share_{BO}$ across all sectors A and B . This results in the $SkillsCorrelation_{AB}$ variable.

3.3 Technology spillovers

Of the three main agglomerative forces technology spillovers are the hardest to quantify or measure. Measuring the flow of ideas between industries is difficult although a number of different proxies have been used in the literature. Audretsch and Feldman (1996) use industry research and development (R&D), university R&D, and skilled labour as measures of knowledge spillovers. Greenstone et al. (2010) quantify agglomeration spillovers as the change in total factor productivity experienced by incumbent manufacturing firms when a large manufacturing firm locates in the same area. Ellison et al. (2010) use two measures. First, they use a technology matrix similar to the input-output matrix for the USA which captures how R&D activity in one industry flows out to benefit another industry. Second, they use a patent database to construct measures of patents in and out of pairs of sectors. These are however imperfect measures as they only capture official exchanges of technology. It is likely that technology exchanges are more informal or accidental, particularly in a developing country context.

We go further in constructing our measure of technology spillover and use a specially designed module on technology usage in the Vietnamese manufacturing sector included in the 2010 Vietnamese Enterprise Survey. All surveyed manufacturing firms are asked the question ‘Do most contracts include technology transfer from the supplier to the enterprise?’ If they answer yes to this question they are asked whether the technology transfer is mainly ‘intentional and part of the legal contract’, ‘intentional but not part of the legal contract’, or ‘unintentional’. The question therefore captures both formal and accidental or informal technology transfers from the supplier to the enterprise. We construct our technology transfer

variable by calculating the proportion of firms in each sector that answer ‘yes’ to this question and weight this by firm revenue. To construct industry pairings we map each sector’s weighted technology transfer variable to each of the other sectors by interacting it with a measure of the proportion of inputs it buys from the other sectors. In other words, for sector A we multiply the weighted measure of technology transfer for the sector by the proportion of sector A ’s inputs that come from sector B to produce the measure $TechTransfer_{AB}$. If technology transfer from suppliers to firms is common in a sector, then we would expect firms in that sector to locate near their suppliers. Therefore, a positive relationship between our technology variable and the coagglomeration index would provide evidence that technology transfer is an important agglomerative force.

3.4 Natural advantages

In this paper, we hypothesize that clustering may be driven by transport costs, labour market pooling, and technology transfers. In addition, some areas may have natural advantages over others that result in cluster formation that are important to control for in our analysis. For example areas that are rich in minerals will attract clusters of mining companies. Following Ellison and Glaeser (1999) we develop a predicted spatial distribution of firms based upon cost differences between regions (commune/district/province). We construct a set of probabilities for each region which captures the probability that a firm will locate in that region if cost is the only factor in its location decision. From the enterprise survey we take data on the average wage paid by firms and the percentage tax that they pay (calculated by tax paid divided by total revenue). We then express the cost per region as a percentage of the total costs faced by firms in Vietnam. As firms are more likely to locate in a region with lower costs we take the reciprocal of this percentage and compute location probabilities. We then randomly allocate firms to regions in Vietnam using these probabilities. We calculate the colocation measures for this predicted spatial distribution of firms and use this variable as a control for differences in costs across regions in the analysis.

4 Descriptive statistics

Table 3 presents summary statistics for the dependent and explanatory variables used in our analysis. The colocation measure is calculated at the three levels of administrative area. The mean and the maximum values of the colocation measure increase as the size of the administrative area increases as is expected. Descriptive statistics for the EG index calculated at the commune, district, and province levels is also presented. The mean of the EG index is approximately zero. This is largely by definition as x_m , the measure of an area’s ‘size’, is the share of manufacturing employment, so the deviation of each sector from the benchmark will be approximately uncorrelated with the average of the deviations of all other industries (Ellison et al. 2010).

The natural advantage proxy (i.e. colocation calculated for the hypothetical spatial distribution of firms, generated based purely on costs) is of a much lower magnitude at all regional definitions than for the actual distribution of firms. This suggests that agglomerative forces go beyond pure cost advantages associated with regions. The input-output maximum is expressed as a fraction and so is bound by 0 and 1. It has a mean of 0.046 which means that, on average, approximately 5 per cent of inputs/outputs are supplied/purchased between sector pairs. This is much higher than Ellison et al.’s (2010) measure for the USA of 0.007 suggesting that, on average, less than 1 per cent of inputs/output are traded between 3-digit sector pairs. Our data also reveal that there are a number of sectors that do not buy or sell any

goods to one another. The maximum, however, is high at 0.893 suggesting that there is a lot of variation between sector pairs in the extent of input-output linkages and some sectors are particularly well integrated.¹¹

The skills correlation measure is bound by -1 and 1, where 1 is perfect positive correlation. The mean value is 0.46 suggesting a relatively high degree of correlation in the types of workers that different sectors employ. This measure is also comparable to Ellison et al. (2010) who find a mean of 0.47 in the correlation between occupation types among sectors. Finally, the technology transfer variable, which is weighted by revenue, has a mean of 0.002, a minimum of zero (implying that no technology transfers occur between some sectors) and a maximum of 0.124. The higher this value is the greater are the technology linkages between sectors.

5 Empirical results

Our core empirical model is given in equation (4).¹²

$$\begin{aligned} Colocation_{AB} = & \beta_0 + \beta_1 CostColocation_{AB} + \beta_2 InputOutput_{AB} \\ & + \beta_3 TechTransfer_{AB} + \beta_4 SkillsCorrelation_{AB} + e \end{aligned} \quad (4)$$

Each of the variables are transformed to have unit standard deviation for ease of comparison of the estimated coefficients on each of the different variables, and to assess the relative importance of each factor in explaining overall coagglomeration patterns. As our unit of analysis is sector pairings residuals may be correlated; to correct for the cross-observation correlation in the error terms involving the same sectors, we report bootstrapped standard errors. Bootstrapping also deals with the econometric issues arising from the use of the generated regressor, $CostColocation_{AB}$ (Pagan 1984; Ellison et al. 2010).

Table 4 presents the results of the regressions where $Colocation_{AB}$ and $CostColocation_{AB}$ are measured at different levels of geographical aggregation (commune, district, and province). We find that coagglomeration when measured at the commune level is not determined by cost advantages. The positive and significant coefficient on the input-output index in column (2) suggests that the more linked along the value chain the sectors are the more likely they are to be coagglomerated. Column (3) reveals that the relationship between input-output linkages and coagglomeration may be motivated by technology transfers between firms. This is confirmed in columns (5) and (6) by the fact that when these variables are included together the positive effect on coagglomeration is solely due to the technology transfer variable. This

¹¹ Ellison et al. (2010) find a maximum of 0.823 for their measure of input-output linkages between 3-digit sector pairs in the USA.

¹² This model is estimated using ordinary least squares. We also estimate a generalized linear model which imposes a logistic distribution on the dependent variable and achieve the same results.

result also holds when the output-index, the input-index, and the absolute input/output values are considered in isolation (results available on request). At the commune level our results suggest that a one unit standard deviation increase in the technology transfer variable is associated with a 0.215 standard deviations increase in the colocation value. Technology transfers are the most important agglomerative force at the commune level.

In contrast to expectations we find that the correlation in occupations across sectors has a negative effect on the extent of coagglomeration. This means that in Vietnam sectors requiring similar skill sets are not likely to locate close to each other. There are two possible explanations for this. First, employers may believe that by locating close to other firms that demand similar skills of their workers, they run the risk of their employees being poached by other firms. Second, if specific skills are in high demand within a commune it will place upward pressure on wages which firms will try to avoid. In other words, the negative relationship between the labour correlation variable and coagglomeration suggests that firms are competing for labour rather than pooling labour. Locating in the same area as firms who employ similar types of workers can lead to the loss of some key workers to competing firms and a higher wage bill to retain others. Our results suggest that correlations in skills demand across sectors is a deterrent to colocation within communes.

Focusing on the district level we find in contrast to the commune level definition, that natural advantages play a small but significant role in the colocation decision. This may be explained by the fact that cost advantages are similar across communes but not across districts. As such, when the region of analysis is the district, natural advantages will play a greater role. The role of technology transfer remains robust to the district level definition of coagglomeration suggesting that even for larger geographical units technology transfer plays an important role in the location choice of firms. A negative relationship is also found between the labour correlation measure and the coagglomeration index giving further support to our suggestion that firms compete for labour and factor this into their location decisions. Labour correlation effects are larger when measured at the district level while technology transfer effects are smaller; a one standard deviation increase of technology transfer is associated with a 0.135 standard deviation increase in colocation while a unit standard deviation increase in the labour correlation is associated with a 0.230 standard deviation decrease in colocation. The results for the province level definition reveal that cost advantages no longer explain the level of coagglomeration. Taken with the results for the commune and district levels, this suggest that natural advantages are not a consideration made by firms in deciding either which province to locate in or which specific commune within provinces to locate in, but are a factor in deciding between districts. The important role of technology transfers is once again evident in the province level regressions as is the negative relationship between the labour correlation variable and coagglomeration.

We also consider the absolute measure of colocation given in equation (3). We substitute this absolute measure for the relative measure in our regression equation (4). Table 5 presents the results of this analysis at each of the three levels of geographic area.

In contrast to our results when using the relative measure of coagglomeration, we find that natural cost advantages are the largest agglomerative force at all three areas of measurement. This result is unsurprising when we think of clustering in absolute terms. Firms in large industries face more competition and so care more about costs than firms in less competitive industries with fewer firms. The absolute measure captures this effect at all three levels of aggregation and the magnitude of the effect is greatest when measured at the province level. This makes sense as cost differences are greatest across provinces. The results for input-output links, technology transfer and skills correlation are in agreement with those found when using the relative measure of coagglomeration; input-output links are not significant at

any level of measurement; skills correlations are significant and negative at all three levels increasing in magnitude with increasing geographic area; technology transfer is positive, significant, and decreasing with increasing geographic area. These results suggest that even if we think of clustering in absolute terms, technology transfers and skills correlations are important coagglomeration forces in Vietnam.

The above summarizes our econometric analysis of agglomeration in Vietnam as we have defined it. We now turn to bringing into focus how our results differ from the results that would emerge based on the EG approach. We therefore substitute the EG measure of agglomeration (γ_{AB}) given in equation (1) for our measure in the empirical model given in equation (4). Table 6 presents the results of this analysis for all three levels of geographical aggregation.

As before, all variables are normalized to have a standard deviation of one for ease of comparison and bootstrapped standard errors are reported in parenthesis. At the commune level, only the measures of technology transfer and skills correlations are found to be statistically significant agglomerative forces; skills correlations is the stronger of the two. Contrary to the analysis using our measure, the labour correlation variable is found to have a positive effect on the EG measure of coagglomeration. This effect is also evident, decreasing in magnitude, at the district and province levels. In contrast with our results above, technology transfers, although significant at the commune level, are small in magnitude. The effect of the technology transfers at the commune level is almost five times larger when the colocation index is used to measure agglomeration. At the district and province levels, the analysis using the EG measure does not find any evidence that technology transfers are a significant agglomerative force. This is in direct contradiction with our results above as well as our understanding of agglomeration processes in Vietnam.

We find no evidence that input-output linkages are a significant agglomerative force using either measure of coagglomeration.¹³ This does not necessarily mean that transport costs and proximity to suppliers or customers are not an important factor in firms' location decisions. Our results only suggest that firms do not locate near *domestic* suppliers or customers in other sectors. Input-output linkages may, however, be a force for *within* sector coagglomeration. Additionally, firms that import their inputs or export their outputs may consider transport costs in their location decisions and so locate near to ports or airports; this is not captured by our input-output measure.

To investigate further and in particular to explore the role of technology transfers, we split the sample into high-tech and low-tech sectors. We consider three sub-sets of sector pairings: (i) both sectors are low-tech; (ii) both sectors are high-tech; and (iii) the two sectors are respectively high- and low-tech. Table 7 shows the results for each pairing when our colocation measure is used as the dependent variable.

For low-tech sector pairings the technology transfer variable is not significant at the commune, district, or province levels suggesting that no technology transfers occur between low-tech firms. The labour correlation measure is negative and significant and increases as the area increases from commune to province. This implies importantly that low-tech firms choose to locate away from other low-tech firms with similar skills requirements, so these firms compete for, rather than pool, unskilled workers. Natural cost advantages are a significant positive force at the commune and district levels but not at the province levels. This means that low-tech firms consider cost differences between regions when deciding in

¹³ We run the analysis using each of the three relative input-output measures and the absolute input-output measure described in section 3.1 and we find no significant effect on coagglomeration.

which commune or district to locate but cost differences do not play a role in province locations.

For high-tech sector pairings the technology transfer coefficient is positive and statistically significant at all three geographical levels, decreasing in magnitude as the area increases. The magnitude of the impact of technology transfers is greater for the high-tech sector pairings than for the whole data set and is the most important agglomerative force for high-tech firms. The labour correlation coefficient is positive and significant at the commune and district levels. This suggests that high-tech firms locate close to other high-tech firms with similar skills requirements and consequently pools of skilled workers emerge in agreement with Ellison et al.'s (2010) findings for the USA.

For mixed sector pairs, the technology transfer coefficient is also positive and significant at all three levels and decreases with the size of area. This suggests that technology transfers occur from high-tech to low-tech firms. As we would expect the magnitude of the technology transfer force is smaller between high- and low-tech sectors than for the high-tech sector pairings. The labour correlation coefficient is negative which implies that if a high-tech firm has similar labour requirements to a low-tech firm they are more likely to locate in different geographic areas. This is further evidence that firms compete for unskilled labour; if a high-tech firm has similar labour requirements to a low-tech firm this is likely because the high-tech firm requires a large number of unskilled workers. For example computer manufacturers may require low-skilled workers for assembly line or packaging tasks. If the high-tech firm has low-skilled worker requirements then they locate in areas where there are fewer low-tech firms and hence low-skilled workers are cheaper and more abundant.

We finally conduct the analysis for the three subsets of sector pairings using the EG measure as the dependent variable. Table 8 shows the results.

First, for low-tech pairings natural cost advantages are significant at the commune and district levels but not at the province level, and are the only significant agglomerative force. Contrary to the results when using our index there is no evidence of low-tech firms competing for unskilled workers. Second, for high-tech pairings, technology transfers are significant only at the commune level, and small in magnitude; once again the effect of the technology transfers for high-tech firms is almost five times larger when the colocation index is used to measure agglomeration. This reinforces our understanding that the EG measure does not capture the important role of technology transfers between high-tech firms as an agglomerative force, nor does it adequately capture the pooling of skilled labour. Third, for mixed sector pairings, skills correlations are a positive force at the commune and district levels. This is in contrast to the results using our measure of agglomeration; labour pooling rather than labour competition appears as a driving force, while technology transfers from high-tech to low-tech firms are not captured.

6 Discussion and conclusion

Understanding firm agglomeration is analytically challenging and the existing empirical evidence is fragmented and scarce. Ellison et al. (2010) advanced the literature by putting forward a coherent overall framework linking agglomeration to three drivers in the case of the USA: transport costs, labour pooling, and technology transfers. In this paper, we have explored the implications of an alternative coagglomeration measure for our understanding of the impact of agglomerative forces. We also developed a measure of technology transfers that encompasses both formal and informal channels which we believe are important in developing country contexts. Furthermore, we disaggregated how agglomeration forces differ

for high-tech and low-tech sector pairings. Our contribution was made possible by an unusually rich set of data for Vietnam. Interesting differences in results emerge. The two major differences between the analysis using the EG index and the analysis using our measure are the ways in which technology transfer and labour pooling impact on agglomeration. First, using our measure we find that technology transfers are an important agglomerative force. The magnitude of the force decreases the larger the geographical area considered, consistent with expectations. When the EG measure is used the technology transfer variable plays a negligible role. This notable difference can be explained by the fact that technology spillovers need not necessarily depend on the number of employees in a firm but could take place between many small firms that form a cluster. In fact, in developing countries, firms that are more technologically advanced may have fewer employees.¹⁴ Large firms tend to be labour-intensive simply because they use low levels of technology and employ large amounts of unskilled labour. Therefore the EG measure, by construction, will not capture the effect of technology spillovers on coagglomeration choices of these firms. The results of the high-tech/low-tech split suggest that technology transfers are an important agglomerative force between high-tech sectors and also between high-tech and low-tech sectors. As might be expected, technology transfers are not found to be an agglomerative force for low-tech sectors. This is consistent with the results for the EG measure which gives greater weight to larger low-tech firms in its construction.

Second, using our agglomeration measure we find a negative and significant effect of the skills correlation variable on coagglomeration. When the data are split into high-tech/low-tech sector pairings, it emerges that the pooling of skilled labour is an important agglomerative force for high-tech firms. In contrast, we have shown that low-tech firms compete for unskilled labour and that the competition intensifies as the region size increases from commune to district to province. When we use the EG index as the measure of coagglomeration, the opposite result emerges. This is contrary to our understanding of the mobility of labour in Vietnam where restrictions on the movement of workers are in place, particularly at the province and district levels. Moreover, this result may also reflect the priorities of the Vietnamese Government as reflected in the *Vietnam Strategy for Socioeconomic Development 2001-2010* (Government of Vietnam nd) in which the government explicitly states that they will encourage labour-intensive firms to locate in rural areas in order to boost employment in rural regions. If labour-intensive firms are incentivized to locate in rural areas where there are smaller populations and therefore fewer workers, they will necessarily choose to locate in rural areas where there are no firms or few firms with similar labour needs.

We also consider an absolute measure of coagglomeration. We find that natural cost advantages are the most important agglomerative force when we think of clusters in absolute terms. We also find that technology transfers are an important positive agglomerative force and skills correlation is a significant negative agglomerative force, in agreement with our results using the relative measure.

Understanding the driving forces behind agglomeration is analytically challenging. It is also critical for governments in the formulation of industrial policy. We have shown that the definition and measurement of agglomeration are crucial to analytical outcomes when agglomeration is linked to underlying driving forces. Ellison et al. (2010) use a measure of coagglomeration that captures correlations in the relative size of two sectors, in terms of employment, across areas. While this may explain an important part of the agglomeration

¹⁴ In our data the mean number of employees for a high-tech firm is 92 while the mean number of employees for a low-tech firm is 143.

story, in a developing country context high-tech sectors tend to be smaller in terms of employment, and within high-tech sectors the more technologically advanced firms tend to be even smaller again. In this setting, the EG index fails to capture the relative importance of high-tech clusters. This is certainly the case in Vietnam. It is left for future research to establish the extent to which the differences we observe reflect underlying characteristics of developed vs. developing country contexts (i.e. USA vs. Vietnam) or are embedded in the way in which agglomeration is defined and measured.

Appendix

Description of manufacturing sector codes

- 1 Production, processing, and preserving of meat and meat products
- 2 Processing and preserving of fish and fish products
- 3 Processing and preserving of fruit and vegetables
- 4 Manufacture of vegetables and animal oils and fats
- 5 Manufacture of milk and dairy products
- 6 Processing of rice and flour
- 7 Other food manufacturing
- 8 Manufacture of prepared feeds for animals
- 9 Manufacture of cakes, jams, candy, coca, chocolate products
- 10 Manufacture of sugar
- 11 Manufacture of alcohol and liquors
- 12 Manufacture of beer
- 13 Manufacture of alcohol-free beverages like soft drinks, mineral waters
- 14 Manufacture of cigarettes and other tobacco products
- 15 Manufacture of fiber (all kinds)
- 16 Manufacture of textile products (all kinds)
- 17 Manufacture of ready-made apparel (all kinds)
- 18 Manufacture of leather and leather products
- 19 Manufacture of wood and by-products
- 20 Manufacture of pulp, paper, and by-products
- 21 Publishing
- 22 Printing
- 23 Manufacture of coke, coal, and other by-products
- 24 Manufacture of gasoline and lubricants
- 25 Manufacture of fertilizers
- 26 Manufacture of other chemical products
- 27 Manufacture of pharmaceuticals, medicinal chemicals, and botanical products
- 28 Manufacture of processed rubber and by-products
- 29 Manufacture of plastic and by-products
- 30 Manufacture of glass and by-products
- 31 Manufacture of other non-metallic mineral products
- 32 Manufacture of cement and cement products
- 33 Manufacture of metal and metal products
- 34 Manufacture of general purpose machinery
- 35 Manufacture of special purpose machinery
- 36 Manufacture of domestic appliances
- 37 Manufacture of electrical machinery
- 38 Manufacture of electrical equipment
- 39 Manufacture of machinery used for broadcasting, television, and information activities
- 40 Manufacture of medical and surgical equipment

- 41 Manufacture of precision and optical equipment
 - 42 Manufacture of transportation machinery and equipment
 - 43 Manufacture of other goods
-

Source: Authors' calculations.

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Table 1: Highest colocation pairings

Sector 1	Sector 2	Commune
05 Milk and dairy products	39 Machinery used for broadcasting, television, and information activities	0.005
26 Chemical products	39 Machinery used for broadcasting, television, and information activities	0.005
28 Processed rubber and by-products	37 Electrical machinery	0.005
37 Electrical machinery	41 Precision and optical equipment	0.004
26 Chemical products	28 Processed rubber and by-products	0.004
36 Domestic appliances	39 Machinery used for broadcasting, television, and information activities	0.004
26 Chemical products	37 Electrical machinery	0.004
27 Pharmaceuticals, medicinal chemicals, and botanical products	39 Machinery used for broadcasting, television, and information activities	0.004
21 Publishing	40 Medical and surgical equipment	0.004
36 Domestic appliances	41 Precision and optical equipment	0.004
Sector 1	Sector 2	District
29 Plastic and by-products	36 Domestic appliances	0.030
22 Printing	40 Medical and surgical equipment	0.027
36 Domestic appliances	39 Machinery used for broadcasting, television, and information activities	0.027
21 Publishing	40 Medical and surgical equipment	0.027
21 Publishing	41 Precision and optical equipment	0.027
18 Leather and leather products	36 Domestic appliances	0.026
36 Domestic appliances	41 Precision and optical equipment	0.026

21 Publishing	22 Printing	0.025
05 Milk and dairy products	36 Domestic appliances	0.025
17 Ready-made apparel	36 Domestic appliances	0.025

Sector 1	Sector 2	Province
36 Domestic appliances	41 Precision and optical equipment	0.410
17 Ready-made apparel	36 Domestic appliances	0.367
17 Ready-made apparel	41 Precision and optical equipment	0.346
05 Milk and dairy products	36 Domestic appliances	0.342
29 Plastic and by-products	36 Domestic appliances	0.340
18 Leather and leather products	36 Domestic appliances	0.336
21 Publishing	41 Precision and optical equipment	0.328
22 Printing	41 Precision and optical equipment	0.327
29 Plastic and by-products	41 Precision and optical equipment	0.325
05 Milk and dairy products	41 Precision and optical equipment	0.318

Source: Authors' calculations.

Table 2: Highest pairings using EG Index

Sector 1	Sector 2	Commune
37 Electrical machinery	41 Precision and optical equipment	0.084
08 Prepared feeds for animals	41 Precision and optical equipment	0.055
04 Vegetable and animal oils and fats	39 Machinery used for broadcasting, television, and information activities	0.040
38 Electrical equipment	41 Precision and optical equipment	0.038
01 Production, processing, and preserving of meat and meat products	05 Milk and dairy products	0.037
36 Domestic appliances	41 Precision and optical equipment	0.029
05 Milk and dairy products	21 Publishing	0.027
08 Prepared feeds for animals	37 Electrical machinery	0.023
34 General purpose machinery	40 Medical and surgical equipment	0.022
05 Milk and dairy products	28 Processed rubber and by-products	0.021
Sector 1	Sector 2	District
37 Electrical machinery	41 Precision and optical equipment	0.143
05 Milk and dairy products	21 Publishing	0.073
08 Prepared feeds for animals	37 Electrical machinery	0.061
08 Prepared feeds for animals	41 Precision and optical equipment	0.059
01 Production, processing, and preserving of meat and meat products	05 Milk and dairy products	0.039
01 Production, processing, and preserving of meat and meat products	21 Publishing	0.035
04 Vegetable and animal oils and fats	39 Machinery used for broadcasting, television, and information activities	0.035
38 Electrical equipment	41 Precision and optical equipment	0.030
34 General purpose machinery	40 Medical and surgical equipment	0.030
01 Production, processing, and preserving of meat and meat products	25 Fertilizers	0.028

Sector 1	Sector 2	Province
01 Production, processing, and preserving of meat and meat products	05 Milk and dairy products	0.194
37 Electrical machinery	41 Precision and optical equipment	0.124
01 Production, processing, and preserving of meat and meat products	21 Publishing	0.123
11 Alcohol and liquors	35 Special purpose machinery	0.121
02 Processing and preserving of fish and fish products	06 Processing of rice and flour	0.100
21 Publishing	22 Printing	0.099
11 Alcohol and liquors	21 Publishing	0.095
04 Vegetable and animal oils and fats	05 Milk and dairy products	0.085
01 Production, processing, and preserving of meat and meat products	14 Cigarettes and other tobacco products	0.082
05 Milk and dairy products	21 Publishing	0.082

Source: Authors' calculations.

Table 3: Descriptive statistics

	Mean	Std. Dev	Min	Max
<i>Colocation measures</i>				
Colocation (Commune)	0.001	0.001	0.000	0.005
Colocation (District)	0.009	0.005	0.000	0.030
Colocation (Province)	0.110	0.071	0.001	0.410
<i>EG measures</i>				
EG (Commune)	0	0.013	-0.026	0.224
EG (District)	0	0.149	-0.374	0.208
EG (Province)	0	0.338	-0.108	0.247
<i>Natural advantage measures</i>				
Cost advantage (Commune)	0.001	0.0002	0.000	0.002
Cost advantage (District)	0.001	0.0002	0.000	0.002
Cost advantage (Province)	0.016	0.001	0.009	0.032
<i>Marshallian factors</i>				
Input-output maximum	0.046	0.113	0.000	0.893
Technology transfer	0.002	0.009	0.000	0.124
Skills correlation	0.460	0.358	-0.166	1.000

Source: Authors' calculations.

Table 4: Determinants of colocation

	(1)	(2)	(3)	(4)	(5)	(6)
Commune level						
Natural advantage	0.025 (0.032)				0.029 (0.035)	0.020 (0.047)
Input-output maximum		0.069** (0.031)			-0.034 (0.034)	-0.040 (0.035)
Technology transfer			0.178*** (0.055)		0.195*** (0.049)	0.215*** (0.068)
Skills correlation				-0.154*** (0.038)		-0.162*** (0.035)
R-squared	0.001	0.005	0.031	0.025	0.033	0.071
Observations	946	946	903	703	903	703
District level						
Natural advantage	0.080** (0.034)				0.092*** (0.035)	0.089* (0.052)
Input-output maximum		0.043 (0.027)			-0.024 (0.029)	-0.013 (0.037)
Technology transfer			0.111*** (0.045)		0.122*** (0.048)	0.135*** (0.053)
Skills correlation				-0.223*** (0.034)		-0.230*** (0.034)
R-squared	0.006	0.002	0.012	0.048	0.021	0.070
Observations	946	946	903	703	903	703
Province level						
Natural advantage	0.021 (0.036)				0.032 (0.046)	-0.034 (0.067)
Input-output maximum		0.020 (0.028)			-0.035 (0.029)	-0.020 (0.027)
Technology transfer			0.076** (0.034)		0.093** (0.047)	0.105** (0.047)
Skills correlation				-0.313*** (0.033)		-0.319*** (0.041)
R-squared	0.0005	0.0004	0.006	0.093	0.008	0.103
Observations	946	946	903	703	903	703

Notes: Bootstrapped standard errors are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Variables are transformed to have unit standard deviation for ease of interpretation.

Source: Authors' calculations.

Table 5: Determinants of colocation using absolute measure

	(1)	(2)	(3)	(4)	(5)	(6)
Commune level						
Natural advantage	0.874*** (0.080)				0.872*** (0.072)	0.870*** (0.070)
Input-output maximum		0.099** (0.042)			-0.088 (0.021)	-0.011 (0.029)
Technology transfer			0.093** (0.049)		0.078*** (0.029)	0.082** (0.035)
Skills correlation				-0.057 (0.043)		-0.073*** (0.021)
R-squared	0.763	0.013	0.008	0.003	0.767	0.761
Observations	946	946	903	703	903	703
District level						
Natural advantage	0.887*** (0.067)				0.886*** (0.061)	0.892*** (0.073)
Input-output maximum		0.083** (0.041)			-0.010 (0.016)	-0.011 (0.025)
Technology transfer			0.059** (0.030)		0.044** (0.019)	0.053** (0.023)
Skills correlation				-0.072* (0.042)		-0.087*** (0.019)
R-squared	0.787	0.007	0.003	0.003	0.787	0.785
Observations	946	946	903	703	903	703
Province level						
Natural advantage	6.42*** (0.567)				6.33*** (0.571)	6.46*** (0.694)
Input-output maximum		0.064* (0.035)			-0.025 (0.022)	-0.027 (0.027)
Technology transfer			0.047 (0.037)		0.040*** (0.015)	0.046*** (0.018)
Skills correlation				-0.088** (0.042)		-0.100*** (0.021)
R-squared	0.707	0.004	0.002	0.006	0.707	0.705
Observations	946	946	903	703	903	703

Notes: Bootstrapped standard errors are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Variables are transformed to have unit standard deviation for ease of interpretation.

Source: Authors' calculations.

Table 6: Determinants of coagglomeration using EG measure

	(1)	(2)	(3)	(4)	(5)	(6)
Commune level						
Natural advantage	0.184** (0.100)				0.175 (0.108)	0.165 (0.110)
Input-output maximum		-0.004 (0.026)			-0.032 (0.022)	-0.036 (0.023)
Technology transfer			0.038** (0.016)		0.044*** (0.014)	0.046** (0.025)
Skills correlation				0.147*** (0.028)		0.127*** (0.033)
R-squared	0.034	0.000	0.0014	0.031	0.033	0.074
Observations	946	946	903	703	903	703
District level						
Natural advantage	0.124** (0.068)				0.117** (0.061)	0.119** (0.072)
Input-output maximum		0.001 (0.022)			-0.017 (0.025)	-0.013 (0.024)
Technology transfer			0.031** (0.017)		0.033 (0.021)	0.029 (0.027)
Skills correlation				0.102*** (0.027)		0.087*** (0.031)
R-squared	0.0155	0.000	0.0009	0.018	0.015	0.045
Observations	946	946	903	703	903	703
Province level						
Natural advantage	-0.067 (0.046)				-0.041 (0.044)	-0.031 (0.036)
Input-output maximum		0.015 (0.028)			0.014 (0.033)	-0.039 (0.034)
Technology transfer			0.015 (0.019)		0.008 (0.022)	0.036 (0.025)
Skills correlation				0.062* (0.036)		0.065* (0.039)
R-squared	0.0044	0.0002	0.0002	0.076	0.002	0.007
Observations	946	946	903	703	903	703

Notes: Bootstrapped standard errors are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Variables are transformed to have unit standard deviation for ease of interpretation.

Source: Authors' calculations.

Table 7: Determinants of colocation for different technology pairings

	<i>Commune</i>	<i>District</i>	<i>Province</i>
Low-tech			
Natural advantage	0.206*** (0.076)	0.252*** (0.068)	-0.105 (0.100)
Input-output maximum	0.060 (0.070)	0.093 (0.078)	0.087 (0.069)
Technology transfer	-0.083 (0.067)	-0.118 (0.078)	-0.093 (0.083)
Skills correlation	-0.208*** (0.062)	-0.290*** (0.065)	-0.356*** (0.064)
R-squared	0.09	0.16	0.16
Observations	171	171	171
High-tech			
Natural advantage	-0.030 (0.077)	0.026 (0.105)	-0.003 (0.091)
Input-output maximum	-0.108 (0.071)	-0.131 (0.081)	-0.263*** (0.091)
Technology transfer	0.393*** (0.082)	0.282*** (0.065)	0.239*** (0.075)
Skills correlation	0.153** (0.080)	0.144** (0.075)	-0.006 (0.072)
R-squared	0.15	0.08	0.06
Observations	171	171	171
Mixed pairings – high-tech/low-tech			
Natural advantage	0.022 (0.082)	0.098 (0.079)	-0.073 (0.070)
Input-output maximum	-0.028 (0.051)	-0.037 (0.054)	-0.001 (0.057)
Technology transfer	0.157*** (0.047)	0.145*** (0.051)	0.102* (0.060)
Skills correlation	-0.176*** (0.044)	-0.245*** (0.054)	-0.324*** (0.048)
R-squared	0.06	0.09	0.11
Observations	361	361	361

Notes: Robust standard errors are presented in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Variables are transformed to have unit standard deviation for ease of interpretation.

Source: Authors' calculations.

Table 8: Determinants of coagglomeration using EG measure for different technology pairings

	<i>Commune</i>	<i>District</i>	<i>Province</i>
Low-tech			
Natural advantage	0.528*** (0.072)	0.442*** (0.083)	0.007 (0.128)
Input-output maximum	0.005 (0.034)	0.017 (0.066)	-0.088 (0.127)
Technology transfer	0.007 (0.037)	-0.063 (0.068)	-0.004 (0.124)
Skills correlation	0.033 (0.030)	0.041 (0.048)	-0.004 (0.049)
R-squared	0.42	0.18	0.01
Observations	171	171	171
High-tech			
Natural advantage	0.128 (0.098)	0.118 (0.078)	0.062 (0.081)
Input-output maximum	-0.085 (0.053)	-0.031 (0.036)	0.003 (0.060)
Technology transfer	0.084* (0.047)	0.071 (0.051)	0.117 (0.044)
Skills correlation	0.102 (0.081)	0.039 (0.064)	0.052 (0.091)
R-squared	0.07	0.06	0.02
Observations	171	171	171
Mixed pairings – high-tech/low-tech			
Natural advantage	0.152 (0.198)	0.093 (0.089)	-0.084 (0.053)
Input-output maximum	-0.044 (0.031)	0.009 (0.040)	-0.020 (0.042)
Technology transfer	-0.001 (0.043)	0.019 (0.033)	-0.004 (0.046)
Skills correlation	0.128*** (0.045)	0.101*** (0.033)	0.065 (0.050)
R-squared	0.04	0.03	0.01
Observations	361	361	361

Notes: Robust standard errors are presented in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Variables are transformed to have unit standard deviation for ease of interpretation.

Source: Authors' calculations.