Cities Trade Pattern*

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Abstract

This paper analyzes whether larger cities have a different trade pattern than smaller cities. Using export data for Spanish metropolitan areas, we show that larger cities specialize in skill-intensive and complex industries. We also conclude that larger cities reveal a comparative advantage in products that demand cognitive and social skills. Within industries larger cities also export higher quality varieties.

JEL: F11, F14, R12
Keywords: metropolitan areas, trade pattern, exports, Spain, comparative advantage

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1 Introduction

Larger and smaller cities do not only differ in terms of population. They are also different regarding abundance of skills and wages: larger cities are more abundant in skilled workers and pay them higher wages than smaller cities (Glaeser and Resseger, 2010).

Recent theoretical models show that if skilled workers have an incentive to agglomerate, and their productivity raises with the skill-intensity of goods, larger cities should have a comparative advantage in more skill-intensive goods (Davis and Dingel, 2014). If the theory is correct, larger cities comparative advantage in skill-intensive goods should reveal in the productive structure, but also in the international trade pattern. The goal of this paper is to test this latter prediction. Using international trade data of Spanish urban areas for the year 2012 we analyze whether the trade pattern of larger cities is more skill-intensive than the trade pattern of smaller cities. Our results show that the size of the city is correlated with a higher amount of exports in skill-intensive and complex industries. We also show that cities specialize in the export of goods that make intensive use of cognitive skills, social skills and tasks that should be deployable at a short geographic distance. Cities do also show differences in trade patterns within industries. In particular, larger cities specialize in the high-quality segments of goods.

The remainder of the paper is organized as follows. Section 2 presents our econometric specification. Section 3 describes the data and presents some stylized facts between the relationship of city size and skill abundance. Section 4 reports main findings and a series of robustness checks. The last section concludes.

2 Specification

We derive our empirical specification from international trade models developed by Eaton and Kortum (2002), Chor (2010) and Costinot et al. (2012). In particular, Costinot et al. (2012) shows that exports from country i to country j in industry k is governed by the following equation:

$$x_{ij}^k = \frac{(c_i t_{ij}^k / z_i^k)^{-\theta}}{\sum_{i'=1}^{I} (c_{i'} t_{i'j}^k / z_{i'}^k)^{-\theta}} \alpha_j^k \mathbf{W}'_j \mathbf{F}_j \tag{1}$$

In our paper the origin of exports are metropolitan areas, cities for short, so x_{ij}^k denotes exports from city i to country$j$ in sector k; c_i is the unit production cost of city i in industry k; t_{ij}^k is the (iceberg) trade cost from city i to country j in industry k; and z_i^k is the productivity of city i in industry k; θ is intra-industry heterogeneity, which is assumed to be the same in all cities and industries; α_j^k is the share that country j spends in industry k; $\mathbf{W}_j$ is a vector of factor prices in country j and $\mathbf{F}_j$ is a vector of factor endowments in country j.

Following Chor (2010), the log of productivity of city i in product k is explained by:

$$\ln z_i^k = \lambda_i + \mu_k + \sum_{\{l,m\}} \beta_{lm} L_{il} M_{km} \tag{2}$$

where λ_i is a city specific productivity component and μ_k is an industry specific component. The last term in equation (2) is the sum of linear combinations between city (L_{il}) and industry characteristics (M_{km}). These combinations of city and industry attributes determine a city's comparative advantage.

In this paper we analyze whether larger cities trade pattern is different to smaller cities trade pattern. Hence, we only consider one city attribute: size, which is proxy by adult population. The literature has identified different reasons to explain why size might be correlated with exporting some goods and not others. Davis and Dingel (2012) argue that skilled workers raise their productivity if they are able to learn from other skilled workers, which generates an incentive to concentrate skilled workers in large cities. This concentration grants larger cities a comparative advantage in skill-intensive goods Davis and Dingel (2014).

The higher abundance of skilled workers also grant larger cities a comparative advantage in goods that demand the combinations of a large number of skilled tasks, as in Minondo and Requena-Silvente (2013), or the combination of a large number of capabilities, as in Hausmann and Hidalgo (2014). Kok and Weel (2014) argue that some products require physical proximity among the workers performing the tasks; as larger cities concentrate a larger number of workers they should have a comparative advantage in products that demand higher workers' proximity.

Bacolod et al. (2009) show that larger cities reward some skills over others. They show that larger cities have a larger share of occupations demanding cognitive and social skills, and a lower share of occupations that demand physical or motor skills.

If we assume that the industry-specific and origin-destination specific trade cost t_{ij}^k can be decomposed into a destination and industry specific and an origin-destination component

$$t_{ij}^k = t_j^k t_{ij} \tag{3}$$

we can substitute equation (2) in (1) to get the following estimating equation

$$\ln x_{ij}^k = \sum_m \beta_m pop_i M_{km} + \mu_{ij} + \mu_{jk} + \epsilon_{ij}^k \tag{4}$$

where pop_i is the population of city i, μ_{ij} is an origin city-country of destination fixed-effect, μ_{jk} is a country of destination-industry fixed effect, and ϵ_{ij}^k the error term.

In addition to trade specialization across industries, we analyze whether larger cities specialize in high-quality varieties within industries. Following Schott (2004), if there is a relationship between skill-intensity and quality, more skill abundant locations should specialize in high-quality varieties within an industry. To test the validity of this argument, we follow Dingel (2014) and estimate the following equation:

$$\ln p_{ijkm} = \beta_1 pop_i + \beta_2 y_i + \beta_3 \ln dist_{ij} + \mu_m + \mu_{jk} + \epsilon_{ijkm} \tag{5}$$

where p_{ijkm} is the unit value price of exports of industry k transported in mode m from origin city i to destination country j, y_i is the income per capita in city i, and $dist_{ij}$ is the distance between city i and country j.

3 Data

3.1 Identification of urban areas

We use the functional urban areas identified by the OECD for Spain. The OECD follows a three step approach to define functional urban areas OECD (2012). First, they identify densely populated municipalities. Second, they aggregate densely populated municipalities into an urban area if more than 15% of the population of one municipality commutes to work in the other municipality. Finally, municipalities that have a low population density are assigned to an urban area if at least 15% of their employed population work in that urban area.

The OECD identifies 76 urban areas for Spain.[1] Spain has 2 large metropolitan areas: Barcelona and Madrid (with a population of 1.5 million of more), 6 metropolitan areas (with a population between 500,000 and 1.5 million), 22 medium-size urban areas (with a population between 200,000 and 500,000), and 46 small urban areas (with a population below 200,000 people). All the large metropolitan and metropolitan areas, and most of the medium-size urban areas are located around a province (NUTS-3) capital.

[1]The list of urban areas is available at http://www.oecd.org/gov/regional-policy/all.pdf

3.2 Data sources and variables

International Trade Data

The Spanish Revenue Agency provides international trade data for Spanish provinces (NUTS-3) at the Common Nomenclature 8-digit level merchandises.[2] This database provides the value of exports, the quantity exported and the model of transport. The main limitation of this data is that Spanish provinces might encompass more than one metropolitan area or an urban area plus some municipalities that do not belong to any urban area. To determine whether province level international trade data is representative of the an urban area trade pattern, we calculate the share of the urban area exports in total province exports. If the urban area represents more than two-thirds of province exports, we consider that province exports are representative of the urban area trade pattern. To calculate exports at the urban area we use data from SABI. This database, produced by Bureau van Dijk, provides economic and financial information for around 2 million Spanish firms. SABI identifies the municipality in which the firm is located, whether the firm exports or not, and in latest releases, the value of exports as % of total sales. To aggregate exports from municipalities to urban areas, we use the assignment of municipalities into urban areas used by the OECD. As shown in the empirical section, our results are robust to the use of alternative thresholds (50% and 75%) and criteria (population and GDP of the urban area as a share of the province). Table 1 lists the 18 urban areas that meet the 2/3 threshold, which form the sample used for the econometric estimations.

Urban area GDP, Population, Education Level and Occupational Structure

Data on urban area GDP, population and education levels is obtained from the

Data on urban area occupational structure is obtained from the Continuous Sample of Working Lives (Muestra Continua de Vidas Laborales, hereinafter MCVL), provided by the Spanish Ministry of Labor and Social Security. MCVL is a micro-level dataset built upon Spanish administrative records. By means of a simple random sampling system, it consists of a representative sample (4% - 1.2 million individuals) of the population registered with the Social Security administration over the sampling year. The MCVL identifies the municipality in which the firm is located if the population of the municipality is larger than 40,000. It also provides information about the occupation of the worker. Workers performing jobs that require a university degree, high-level managers, and administrative and workshop bosses are included in the high-skill group.

Industry level data

Following Romalis (2004) and Chor (2010) skill-intensity at the industry level is measured as the share of non-production workers over total workforce. This data is obtained

[2] It is available at `http://www.agenciatributaria.es`

from the US Manufacturing Census. We also use other proxies for skill-intensity, such as the share of non-production workers wages in total payroll, industry average wage and the share of workers performing skill-intensive tasks with no change in results.

We use two different variables to proxy industry complexity. The first comes from Hausmann and Hidalgo (2014), which define industry level complexity as the number of capabilities that are needed to produce a good. The number of capabilities is proxy through a iterative process between countries diversification level (number of products that countries export with a revealed comparative advantage) and products ubiquity (number of countries that have a revealed comparative advantage in the product). This data, calculated at the Harmonized System 4-digit level, is available at `http://atlas.cid.harvard.edu/rankings/`. The second variable comes from Minondo and Requena-Silvente (2013), which define complexity as the number of skill-intensive tasks that are combined to produce a good. This data is obtained from the Occupational Employment Statistics (OES) survey of the U.S. Bureau of Labor Statistics (available at `http://www.bls.gov/oes`. We consider as skilled occupations those included between the Standard Occupational Classification (SOC) category 11 and 29: management and other occupations that involve an intensive use of scientific and technical knowledge.

To calculate industries intensity in cognitive, people and connected skills we use the O*NET database (avalilable at `http://www.onetcenter.org/database.html`. O*NET identifies 21 abilities that are related to the cognitive area, and weights the importance of the cognitive ability for each occupation (in a 1 to 5 scale).[3] Following Bacolod et al. (2009), we use a principal component analysis to collapse the 21 abilities into one cognitive skill indicator. We calculate an industry-level cognitive skill-intensity as the sum of all occupations cognitive skill-intensity, weighted by the share of each occupation. We obtain this latter data from OES. We use a similar procedure to calculate the industry level intensity of social skills. In this case the O*NET identifies six different social skills.[4] Finally, we use the Kok and Weel (2014) connectivity index to calculate the connectivity-intensity in each industry. These authors calculate the spatial correlation of the work activities identifies in O*NET (see Table 2 in Kok and Weel (2014)). From these data we calculate the connectivity of each occupation as the average of each work activity, weighted by the importance of the activity in each occupation. Then, we calculate an industry level skills connectivity index as the average of occupations connectivity, weighthed by the share of each occupation in industry employment.

[3]The 21 abilities are category flexibility, deductive reasoning, flexibility of closure, fluency of ideas, inductive reasoning, information ordering, mathematical reasoning, memorization, number facility, oral comprehension, oral expression, originality, perceptual speed, problem sensitivity, selective attention, spatial orientation, speed of closure, time sharing, visualization, written comprehension, and written expression.

[4]These are coordination, instructing, negotiation, persuasion, service orientation and social perceptiveness.

3.3 Stylized Facts

Figure 1 shows the relationship between the share of the population with tertiary education and urban area population.

Figure 2 shows the relationship between the share of the occupied population skill-intensive tasks and urban area population.

4 Results

4.1 Main results

Table 2 presents the results of estimation equation (4). As in Chor (2010) in columns (1)-(3), we estimate the equation with only one variable determining the trade costs between city i and country j. In Columns (4) to (7) we allow for other variables, captured by an origin-destination fixed effect. First, we introduce the interaction variables one by one. The interaction between city population and industry skill-intensity, measured by the share of non-production workers, is positive and statistically significant. This result confirms that larger cities specialize in more skill-intensive goods. The interaction term between Hidalgo and Hausmann (HH) product-complexity and city size, and the interaction term between Minondo-Requena (MR) producti complexity and city size are also positive and statistically significant. These results point out that larger cities specialize in the exports of goods that demand a larger combination of capabilities and skilled tasks. Results are robust to using distance or fixed effects to control for trade costs. In Column (7) we combine the three interaction terms. All of them remain positive and statistically significant.

Table 3 presents the results of estimating equation (5), where industries differ in cognitive skills, social skills and skills that tend to be combined at short geographical distance. The three skill type indicators at the industry level are highly correlated, so we estimate them one by one.[5]. The interaction term between city population and each skill type is positive and statistically significant, concluding that larger cities export goods that are intensive in cognitive skills, in social skills and in tasks that tend to be performed at short geographical distances.

Table 4 presents the results of estimating equation (5), where we analyze whether cities specialize in the high-quality ranges of each industry. In Column (1) we only include distance and population as explanatory variables, along with the different fixed

[5]The correlations between the industry intensity of cognitive skills and social skills is 0.87, the correlation between connectivity and social skills 0.87 and the correlation between cognitive and connecetivity 0.773

effects. The estimation shows that the unit price is positively correlated with the population of the city. Distance is also correlated with a higher unit value, but it is not statistically significant. In Column (3) we introduce urban areas GDP per capita as an additional explanatory variable. We want to test the Lindert hypothesis, which predicts a positive correlation between exporters income per capita and specialization in high-quality varieties. Contrary to expectations we find that income per capita is negatively correlated with the unit price of exports; the population coefficient remains positive and statistically significant. Finally, we analyze whether specialization in high-quality ranges is easier in those goods that allow a larger range of quality varieties. This range is proxy by the index developed by Khandelwal (2010). We interact the quality range index with each of the explanatory variable. As shown in Column (3), all interaction terms are statistically not significant. The population coefficient remains positive and statistically significant.

4.2 Robustness

Table 5 presents the results of estimating equation (4) with BACI data.

5 Conclusions

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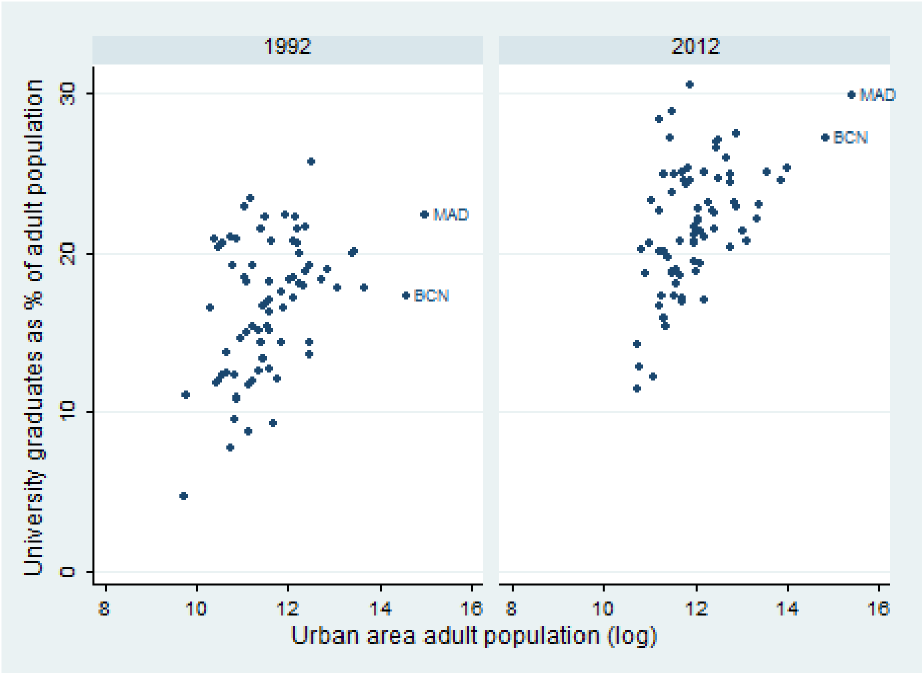
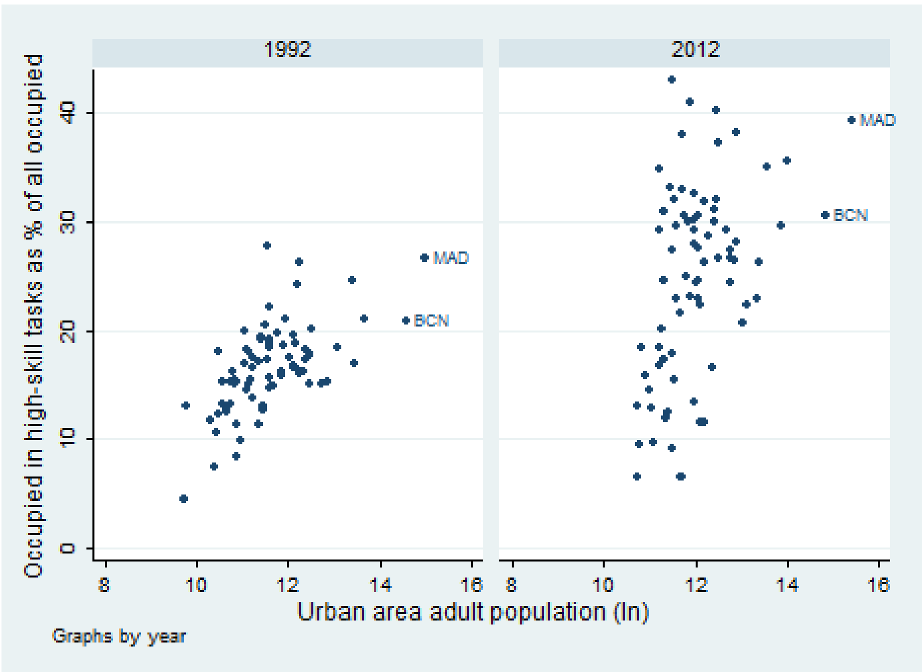
Figure 1: Share of adults with tertiary education and urban area adult population, 1992 and 2012



Source: INE Population Census.

Figure 2: Share of occupied is skilled tasks and urban area population, 1992 and 2012



Source: INE Population Census and Social Security Muestra Continua de Vidas Laborales.

Table 1: Functional urban areas included in the paper

Urban areas	Class type	Population (2012)
Madrid	Large metropolitan area	6719100
Barcelona	Large metropolitan area	3738273
Valencia	Metropolitan area	1603500
Sevilla	Metropolitan area	1446746
Bilbao	Metropolitan area	1002679
Las Palmas	Metropolitan area	666210
Mallorca	Medium-size urban area	620907
Tenerife	Medium-size urban area	506612
Valladolid	Medium-size urban area	459207
Vigo	Medium-size urban area	453342
Pamplona	Medium-size urban area	399704
Cordoba	Medium-size urban area	364567
Cadiz	Medium-size urban area	343197
Salamanca	Medium-size urban area	251553
Leon	Medium-size urban area	250374
Logrono	Small urban area	207256
Albacete	Small urban area	199708
Ourense	Small urban area	191613

Table 2: Cities population and export specialization in skill-intensive and complex industries

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Distance (ln)	-1.963***	-1.965***	-1.960***				
	(0.200)	(0.201)	(0.200)				
Share production workers * ln(pop)	0.0186***			0.0207***			0.0132***
	(0.000842)			(0.000829)			(0.000914)
HH complexity * ln(pop)		0.112***			0.127***		0.0766***
		(0.00590)			(0.00587)		(0.00620)
MR complexity * ln(pop)			0.0461***			0.0552***	0.0216***
			(0.00250)			(0.00238)	(0.00261)
R^2	0.466	0.465	0.464	0.517	0.516	0.516	0.519
Observations	168254	168254	168254	168254	168254	168254	168254

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Regressions on different skill types

	(1)	(2)	(3)
Cognitive skills * ln(pop)	0.165***		
	(0.00830)		
Social skills * ln(pop)		0.387***	
		(0.0163)	
Connectivity * ln(pop)			0.0623***
			(0.00215)
R^2	0.516	0.517	0.520
Observations	168254	168254	168254

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: City population and exports of high-quality goods

	(1)	(2)	(3)
Distance (ln)	0.0582	0.0497	0.0492
	(0.0402)	(0.0408)	(0.0740)
Population (ln)	0.0291***	0.0515***	0.0488**
	(0.00789)	(0.0118)	(0.0214)
GDP per capita (ln)		-0.153**	-0.222*
		(0.0702)	(0.122)
Distance (ln)*Quality			-0.00568
			(0.0267)
Population (ln)*Quality			0.00549
			(0.00718)
GDP per capita (ln)*Quality			0.00413
			(0.0392)
R^2	0.789	0.789	0.763
Observations	389181	389181	259287

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Regressions using BACI data

	(1)	(2)	(3)	(4)	(5)	(6)
ln(Average wage) * ln(pop)	0.454***					
	(0.111)					
HH complexity * ln(pop)		0.0263				
		(0.0307)				
MR complexity * ln(pop)			0.0345***			
			(0.00698)			
Cognitive skills * ln(pop)				0.127***		
				(0.0272)		
Social skills * ln(pop)					0.196***	
					(0.0373)	
Connectivity * ln(pop)						0.0246***
						(0.00445)
R^2	0.347	0.287	0.344	0.343	0.346	0.345
Observations	2892	1621	3070	3070	3070	3070

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$