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Smart Cities are Big Cities
Comparative Advantage in Chinese Cities

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Abstract

The literature on China indicates that the concentration of economic activities in China is less than in other industrialized countries. Institutional limits are largely held responsible for this finding (e.g. the Hukou system); firms and workers are not able to take full advantage of the benefits from agglomeration economies. China is changing rapidly, however, also in this respect. We show that, by using the methodology developed by Davis and Dingel (2013), high-skilled workers in high-skill intensive sectors sort into larger locations. We demonstrate this for regions, agglomerations, cities, and for skills, occupations, and sectors. The results are strongest for cities and skills, followed by agglomerations and occupations, respectively. Between 2000 and 2010 this sorting process has become stronger, which we interpret as an indication that institutional limitations in China against further agglomeration weaken, and that the consensus in the literature that 'Chinese cities are too small' needs some qualification.

JEL-Code: R110, R120, J610, L700.

Keywords: urban specialization, skill concentration, agglomeration economies.

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1 Introduction

China has seen a dramatic transition from a central planned economy to a market-oriented economy since 1978. What seems striking, however, in the development in China during this renewed period of economic reform is that agglomeration of economic activity in relative terms lags behind other countries.[1] Lu and Tao (2009, p. 167), for instance, note that 'industrial agglomeration in China...has increased steadily…though it is still much lower than those of selected developed countries such as France, United Kingdom, and the United States.' In similar vein Fujita et al. (2004, p. 2955) observe that the Gini-coefficient for China is 0.43, which is 'way below the world [average]...Only former Sovjet bloc countries have similarly low Gini's, Russia with 0.45 and Ukraine with 0.40.' Institutional restrictions on internal migration, notably the Hukou system, are largely held responsible for this outcome.[2] The consensus in the literature seems to be that China is under-urbanized, a point strongly put forward by Au and Henderson (2006a,b).

We present evidence that this consensus needs to be qualified. The Hukou system is relaxed and the Chinese labor force has increasingly become mobile across regions. Agricultural reforms have made it possible for farmers to enter cities (Zhu and Luo, 2010). The development of private enterprises enabled rural-urban migrants to seek jobs and earn their living in cities (Zhu and Luo, 2010). The rise in rural-urban income inequalities has stimulated migration, also of informal migration to urban areas (Zhang and Song, 2003; Du, Park and Wang, 2005; Chen, Jin and Yue, 2010; Bosker et al. 2012; Combes et al., 2013). Recent micro firm location data indicate that the conclusions with respect to economic agglomeration in China, such as stated in Fujita et al. (2004), might no longer be valid or need to be qualified. Brakman et al. (2014), for example, observe strong localization of manufacturing firms in China by applying the so-called Duranton-Overman index to firm location data. Moreover, these localization patterns in China are stronger than usually found for UK or Japan, and comparable to those of the US; these findings indicate that also in China firms try to benefit from agglomeration economics. This evidence is consistent with Ge (2009) who finds that export-oriented and foreign-investment sectors have a higher degree of

[1] For an in depth survey on China's economic history see Brandt et al. (2014).

[2] The Hukou system, which is unique for China, is a visa system that regulates rural-urban migration. For a description what it (still) implies in practice, see The Economist (2010), from which it is clear that restrictions are present and restrict migration (see also Bosker et al. 2012). The Chinese government is currently taking measures to relax the hukou system. Other institutional limitations related to economic planning might also interfere with market forces.

agglomeration than other sectors in the period 1985 to 2005.[3] Also high-skill workers migrate from low wage cities to high wage cities that are characterized by a large concentration of human capital and technological changes (Fu and Gabriel, 2012). Combining the findings on firm and worker location suggests that the notion that China is under-agglomerated is no longer a fitting description of recent location and migration trends. The contribution of this paper is that we provide alternative evidence to show for China that larger cities are becoming skill-abundant and specialize in skill-intensive activities, which is another indication that China is rapidly liberalizing and that institutional limits to agglomeration are weakening.

Based on the theoretical framework developed by Davis and Dingel (2013) and using data from the Chinese census of population in 2000 and 2010, we employ an elasticity regression test and a non-parametric pairwise comparison test to identify the interactive relationships between location size for skills, sectors, and occupations for Chinese locations in 2000 and 2010. The results of both tests show that larger locations are relatively more skill abundant in both 2000 and 2010. The results for sectors and occupations confirm this only in 2010, however. This is an indication that the Chinese economy is becoming more market-oriented over time and that agglomeration economies are increasingly allowed to work.

The remainder of this paper is organized as follows. Section 2 reviews the related studies and the theoretical framework. Section 3 sets out the methodology of the elasticity test and the pairwise comparison test. Section 4 discusses data sources. Section 5 presents the results on the relationships between location size for skills, sectors, and occupations. Section 6 offers concluding remarks.

2 Theoretical framework

2.1 Related studies

This paper is related to two strands of literature. One strand of literature focuses on agglomeration economies (see Rosenthal and Strange, 2004). These can be stimulated by a division of labour and skills across cities.

Glaeser (1999), Mori and Turrini (2005), Glaeser and Resseger (2010), Duranton and Jayet (2011), for instance, find that workers of higher skills are inclined to live in larger cities.

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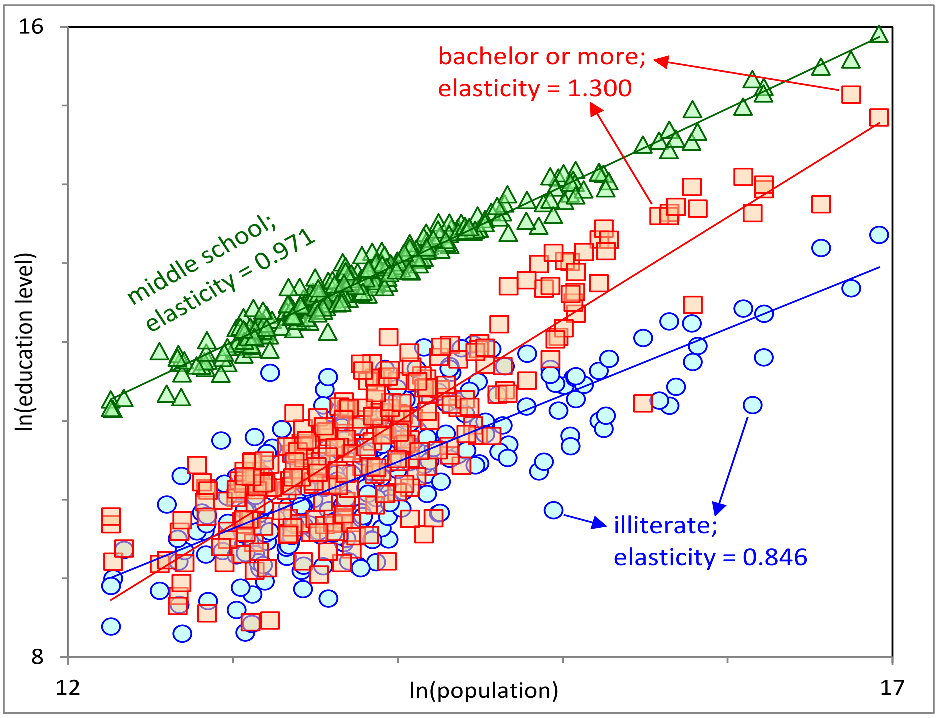
[3] Brakman et al. (2014) analyze localization patterns of Chinese firms for the period 2002-2008 and differentiate between: various types of ownership, new entrants, and large versus small firms. Only for state-owned firms localization is limited.

These studies measure skill by educational levels. Bacolod, et al. (2009) instead, group workers according to occupations (for US workers), that is, cognitive, people, and motor skills. They find that higher cognitive skills tend to concentrate in more dense cities (see also, Michaels et al., 2013).

Recent research points towards a sorting process of higher skills with location size. Life in bigger cities is more expensive, more competitive and selection among individuals is tougher, which implies that only the most talented or productive people are able to afford to live there (see Combes et al. 2012, or Behrens et al., 2013, for an overview of this literature).[4] The implication is that bigger cities are not only more productive than smaller cities because of agglomeration economies, but also because more productive people or firms sort into bigger cities. Figure 1, provides a simple illustration for China in 2010.

Figure 1: Selected skill sorting as measured by education level in cities; China, 2010



Source: Chinese census of population, 2010; vertical axis depicts the log of the number of people with a certain education level living in the city; see the main text for details

Differentiating between three education levels: illiterate (circles), middle school (triangles), and bachelor-or-more (squares), we observe a positive relation between city population and all education levels, but the slope of the bachelor-or-more line is significantly higher

[4] Note, that we do not discuss skill productivity and skill complementarity as in Eeckhout et al. (2014). They find for the US evidence of skill complementarity in the sense that 'the productivity of the high-skilled is enhanced by the providers of low-skilled services, (p.601)', which to a large extent explains urban wage premia for high-skilled workers. In line with their results we find evidence of a disproportionally large share of high-skills in large cities, but do not find evidence of a disproportionally high share of low(est) skills in large Chinese cities.

compared to illiterate and middle school levels. For the current paper the causality between location size and agglomeration economies is not a key issue because we are interested in the relationship between location size and the sorting of skills, as well as its evolution over time, independent of a particular causal relation.

A second strand of literature focusses on the sector distribution across cities. The classic reference is Henderson (1974). He argues that the optimal city size is characterized by the trade-off between the benefits and costs of laborers. This trade-off varies with the type of specialized production in the city due to different degrees of economies of scale across sectors. Henderson (1983), using data for the United States in 1970 and a 'back-of-the-envelope' method, investigates how employment of an industry varies with city size. He finds that manufacturing activities appear to concentrate in larger cities, especially the white-collar sectors, business services, and the sectors finance, insurance and real estate, with the exception of resource-based manufacturing which tends to decline with city size. Henderson (1997) extends the empirical work to other economies, such as Brazil, Japan and Korea, finding similar production patterns in all of these countries: medium-size cities tend to be relatively more specialized in manufacturing activities, especially in the low-skill intensive industries, while the larger cities tend to contain the high-tech and diversified manufactures, business services, and R&D activities. He attributes the reason for the second pattern to the large demand for local diverse labor and product markets for these economic activities. Holmes and Stevens (2004) empirically examine the spatial distribution of economic activities in North America. They find that agriculture, mining, manufacturing, and utilities concentrate in smaller cities. In contrast, transportation, wholesale trade, real estate, finance & insurance, management, and professional services trend to concentrate in larger cities (consistent with previous studies, see Henderson, 1983 and 1997). Similar research shows comparable patterns of specialization of sectors and industries in bigger or smaller agglomerations (Duranton and Overman, 2005, 2008; Fujita et al., 2004).

The above mentioned two strands of literature are not independent. Concentration of certain skill-levels of workers and of industries in which they are (relatively intensively) employed also brings us in the world of the Heckscher-Ohlin trade model. Courant and Deardorff (1992, 1993) explicitly link international trade patterns to concentration of production factors in certain (urbanized) areas within countries; places that are abundant in specific production factors are home to sectors that use these factors intensively. This 'lumpiness' of production factors within a country might contribute to the explanation of the structure of international trade (see for some empirical support, Brakman and van Marrewijk, 2013). Openness and increased international integration can thus stimulate further agglomeration and specialization of cities; a link that is especially important for an export oriented economy like China. This literature points towards a joint determination of the distributions of skills and sectors across cities.

A large part of the literature on (systems-of-) cities assumes a homogeneous city population and abstracts from labour market heterogeneity (Abdel-Rahman and Anas, 2004). Davis and Dingel (2013) and Behrens et al. (2013), however, develop models of a system-of-cities that allow for greater labour market heterogeneity and explore the joint relationship between the skills distribution across cities and the sector employment distribution across cities. In contrast to the Henderson(1974)-world of specialized and perfectly diversified cities they develop a case in which cities are incompletely specialized, as in Helsley and Strange (2012). Davis and Dingel (2013), rely on urbanization economies and individuals' comparative advantage. They thus endogenize the 'lumpiness' of the production factors which are exogenous in Courant and Deardorff (1992, 1993). The theoretical model of Davis and Dingel (2013) results in testable hypotheses: larger cities will be more skill abundant and specialize in relatively more skill-intensive activities than smaller cities.

Our paper applies the tests of Davis and Dingel (2013) to Chinese locations. If the tests show similar outcomes as those of Davis and Dingel (2013) for the US, this is interpreted by us as an indication that agglomeration economies are also strong in China, and that the economic system in China is supportive of stimulating further agglomeration and specialization. The next section describes the empirical set-up in more detail.

2.2 Model structure

Our empirical work is based on the theoretical model of Davis and Dingel (2013). They develop a fairly general framework in which L heterogeneous individuals with a continuum of skills s sort over a continuum of (intermediate good) sectors σ by choosing from a continuum of locations δ within C discrete cities, $c \in \mathbb{C} = \{1, .., C\}$. Their objective is to maximize utility U, which is equal to disposable income, given by the difference between the individual's value of productivity $\mathrm{q}(\mathrm{c}, \delta, \sigma; \mathrm{s}) p(\sigma)$, where q is productivity and p is the price of the intermediate good, and the rental rate $\mathrm{r}(\mathrm{c}, \delta)$, see equation (1). The rental rate only depends on the city and the location within the city. An individual's productivity depends on the city-level total factor productivity $A(c)$, which is taken as given by the individuals but depends on the city's size and the distribution of skills within the city, interacted with location $D(\delta)$ and the choice of sector combined with skills $H(s, \sigma)$, multiplicatively.

$$U(s, c, \delta, \sigma) = q(.)p(.) - r(.) = A(c)D(\delta)H(s, \sigma)p(\sigma) - r(c, \delta) \qquad (1)$$

As a normalization, higher δ locations in a city are less attractive / productive, so $D'(\delta) < 0$. One can think of commuting costs to the central business district, but an alternative interpretation of the model is the desirability of a location because of its consumption value. The function H is assumed to be strictly log-supermodular (in s and σ) and strictly increasing in skills.[5] This ensures that higher skilled individuals are more productive and also *relatively* more productive in higher σ (more skill-intensive) sectors. Individuals supply one unit of labor inelastically and pay rent to absentee landlords, who engage in Bertrand competition.

In a competitive equilibrium individuals choose location within the city and the sector to work in independently as these enter the objective function separable. We order the system of cities in terms of total factor productivity such that $A(C) \geq A(C-1) \geq .. \geq A(1)$. As $D(\delta)$, indexes the desirability of location δ within a city this, as Davis and Dingel (2013) note, can be interpreted as reflecting the commuting costs to the Central Business District. Define the *attractiveness* γ of a location δ within a city c as: $\gamma = A(c)D(\delta)$. In equilibrium $A(c)D(\delta) = A(c')D(\delta')$. The trade-off between *A(c)* and *D(δ)* implies that one can choose between a not-so-good location in a productive city and a wonderful location in a less productive city. Since the people with the highest skill levels can afford to choose the most attractive locations, there will be a range of high-skilled people living in, say, large Shanghai that cannot be found in smaller Suzhou, followed by a range of people with similar skill levels found in both cities. Since higher-skilled people work in the more skill-intensive sectors, larger cities contain relatively more skill-intensive sectors.

Davis and Dingel (2013) show that, under a regularity condition (namely that the supply of locations in a city is decreasing and log-concave), the distribution of skills over cities (say $f(s, c)$, which is integrated over sectors and locations within the city) is log-supermodular, see equation (2). Moreover, the same holds for output, employment, and revenue from a sector perspective. The inequality in equation (2) satisfies the monotone likelihood ratio property, which means that the relative returns to increasing skills (s) or the skill-intensity of sectors (σ) are increasing in city size (Milgrom, 1981; Costinot, 2009). This allows us to

[5] That is: $s > s', \sigma > \sigma' \Longrightarrow H(s, \sigma)H(s', \sigma') > H(s, \sigma')H(s', \sigma)$.

evaluate the main implications of the model using two simple empirical tests, as discussed in the next section.

$$f(s,c)f(s',c') \geq f(s,c')f(s',c), \quad \text{for } c \geq c' \text{ and } s \geq s' \tag{2}$$

In deriving the above relationship we imposed a competitive equilibrium in which laborers are allowed to move freely. Since China has been engaged in a long transformation process going from a centrally-planned economy to a more market-oriented economy ever since Deng Xiaoping started the Economic Reform process in 1978, we expect the predictive power to improve as time progresses. That is, if institutional limitations such as the Hukou system do not prevent this. Since these restrictions on labor mobility are gradually being lifted (some restrictions are still in place to this day), we expect that the predictive power of the model improves as time progresses. In the discussion below, we will interpret changes over time regarding the predictive power of the model as an indication of China's move to a more market-oriented economy characterized by more labor mobility and firms benefitting from agglomeration economies. To summarize the discussion, we have the following:

Hypotheses. In a competitive equilibrium with mobile workers:

H1: Larger cities are relatively more skill abundant.

H2: Larger cities house relatively more skill-intensive sectors / occupations.

H3: The validity of *H1* and *H2* improves over time.

3 Empirical methodology

To identify the effect of the city size on the (joint) distribution of skilled laborers and skill-intensive sectors, we use two simple empirical tests, namely the "elasticity test" and the "pairwise comparisons test", which both depend on the super-modularity of $f(.)$.

3.1 Elasticity test

Hypotheses 1 and 2 state that larger cities are relatively skill abundant and house relatively more skill-intensive sectors. In other words, the city-population elasticity of the skill type should be increasing in skill levels. Similarly, the city-population elasticity of sector employment should be increasing in the skill intensity of sectors. In our empirical work we order the skill-intensity either by sector σ or by occupation o and use the following regression:

$$lnf(v,c) = \beta_{v0} + \beta_{v1}\alpha_v + \beta_{v2}lnL(c) + \beta_{v3}\,\alpha_v * lnL(c) + \epsilon_{v,c}, \quad where\ v = s, \sigma, o \tag{3}$$

Where s, σ, and o denote the skill level, sector, or occupation, $lnf(v,c)$ is the natural logarithm of the distribution (of skills, sectors, or occupation) across cities, α_v represents the fixed effect, $lnL(c)$ is the natural logarithm of the city population, and the β's are estimated coefficients. If $f(v,c)$ are supermodular functions we have $\beta_{v3} \geq \beta_{v'3} \leftrightarrow v \geq v'$.[6] These elasticities are measured by interacting fixed effects with city population, allowing the impact of city size to depend on different groups of skills, sectors, and occupations.

3.2 Pairwise comparison test; supermodularity

An example illustrates the non-parametric pairwise comparison test.[7] Suppose we have empirical information on the distribution of 4 types of skills, ranked according to skill level, across 40 cities, ranked according to size. We can then directly compare any two arbitrary cities and two skill types to see whether or not inequality (2) holds. If so, we verify that the larger city in this pairwise comparison has relatively more workers of the higher skill type. We call the comparison a 'succes' if the condition holds (value = 1) and a 'failure' if not (value = 0). We can compare 40 cities in $(40 \times 39)/2 = 780$ different pairs, and each city pair has 4 skill types with $(4 \times 3)/2 = 6$ different skill combinations. This gives a total of $780 \times 6 = 4680$ pairwise comparisons. The extent to which the average succes rate exceeds the random distribution benchmark of 0.5 can then be taken as an indication regarding the sorting-predictive power of the model. Similarly, we can construct city pairs if we have various types of sectors or occupations ranked according to skill level in each city.

We expect that the comparison between a very large city (such as Shanghai with 23 million people) and a much smaller city (such as Wuhai in Inner Mongolia with 0.5 million people) to be successful almost surely and to be more revealing to test the prediction than a comparison between two similar-sized cities, such as Wuhai (532,902 persons) and Nujiang (534,337 persons). In the latter case the test outcome might be a random result. We will therefore report 'weighted' success rates, where we use the difference in log population for a city pair as weight. Also, we do not have to restrict ourselves to comparing individual cities. We can also compare groups of cities in 'bins' of different size. Suppose we have two distinct sets of cities C and C' with the smallest city in C being bigger than the biggest city in C' and two skill types with $v > v'$. Inequality (2') then also holds for the bin:

$$\sum_{c \in C} f(v,c) \sum_{c' \in C'} f(v',c') \geq \sum_{c \in C} f(v',c) \sum_{c' \in C'} f(v,c') \qquad (2')$$

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[6] As shown in footnote 24 in Davis and Dingel (2013), this regression can be understood as a first-order Taylor approximation where β_{v3} is increasing in *v*, due to the (log) super modularity of *f(.)*.

This inequality implies that if the cities are grouped into a series of bins ordered by city size, then in any pairwise comparison of two bins and two skills the bin containing the larger cities has relatively more of the high-skilled workers. Similarly for sectors and occupations. When we create 2 bins we have just 1 comparison (large versus small cities). When we create 4 bins we have 6 comparisons, and so on. In the analysis below we divide the cities into 2, 4, 10, 30, 90, and individual bins.[8] If m is the number of bins and n is the number of skills (sectors / occupations) the total number of pairwise comparisons is thus $\frac{m(m-1)}{2} \times \frac{n(n-1)}{2}$. We report both the unweighted and weighted success rate of the pairwise comparisons per bin.[9]

4 Data

4.1 The administrative division of locations

Our primary data sources are the population census of 2000 and the population census of 2010. The administrative division of Mainland China consists of five levels, but our dataset only covers the top three levels: the provincial level, the prefecture level, and the county level.[10] There are different types of county levels, such as 'district' and 'county' proper, where district is urban-based while county is rural-based. We identify three different types of locations, namely two 'city' levels and one 'regional' level to analyze the sorting of skills, sectors, and occupations over different locations. We label these *Regions*, *Agglomerations*, and *Cities*, see Table 1.

The prefecture level is the basis of our spatial units: smaller divisions within a prefecture are aggregated to form a specific spatial unit. As a consequence, the number of cities, agglomerations, and regions would in principle be the same in a given year. However, since certain prefecture levels do not contain districts and/or county-level cities, there is a lower number of cities and agglomerations. More precisely, for the whole country there are 262 cities, 312 agglomerations, and 338 regions in 2000, while there are 284 cities, 316 agglomerations, and 337 regions in 2010.

[8] Individual bins consist of one city per bin.
[9] We use the difference of the log of the average population in a bin as weight. `
[10] Levels 4 and 5 are the township level and the village level.

Table 1: Summary of Chinese administrative division at prefectural and county level

Type			Administrative division	2000			2010		
				Population share (%)	Cum.	Num.	Population share (%)	Cum.	Num.
1	2	3	Prefectural level + Municipalities	98.3		338	98.3		337
		City	District	26.3	26.3	803	34.7	37.7	861
	Agglomeration		County-level city	20.3	46.3	389	17.3	52.0	353
Region			County	48.4		1489	43.3		1460
			Auto. county	2.4		109	2.2		110
			Banner	0.9		52	0.8		52
			Special district	0.0		1	0.0		1
			Adm. committee	-	98.3	-	0.0	98.3	3

Sources: Chinese census of population 2000 and 2010; Auto. = autonomous; Adm. = administrative; Cum. = cumulative percentage; Num. = number of units.

Figure 2 illustrates our procedure for location construction for the Yancheng prefecture in the east-coastal province of Jiangsu (close to Shanghai) in 2010. The area of Yancheng prefecture is almost 17,000 km^2, roughly the size of Swaziland or half the size of the Netherlands. Yancheng prefecture consists of 9 county-level sub-regions, namely 2 districts, 2 county-level cities, and 5 (rural) counties. Yancheng *Region* consists of the population of all 9 counties, or about 7.3 million people in total. Yancheng *Agglomeration* consist of the two districts (Yandu and Tinghu) and the two county-level cities (Dafeng and Dongtai), or about 3.3 million people (46 percent of the total population). Finally, Yancheng *City* only consists of the two districts Yandu and Tinghu, or about 1.6 million people (22 percent of the total population). The definition thus becomes more concentrated and more coherent as we go from Region to Agglomeration to City.[11]

[11] Baum-Snow, et al. (2013) analyze changes in spatial definitions over the 1990-2010 period in detail and observe changes in the definitions over time (f.i. some cities did not exist as a city in 1990, but were defined as such for planning reasons). To deal with this they introduce a ‘constant boundary central city’ for consistency purposes. We, instead, use the official statistical boundaries. The potential bias in our results is limited, because: changes in spatial definitions between 2000-2010 (our sample) are less pronounced than in the 1990-2010 period (Baum-Snow, et al.,2013); we do not compare changes of individual cities over time on a one-to-one bases (but compare distributions), and we do not use – in line with Baum-Snow et al. - the entire prefecture as the ‘city’ definition. Furthermore, a sensitivity analysis suggests that potential biases are limited (see Appendix B).

Figure 2: Yancheng prefecture; Jiangsu province, China, 2010

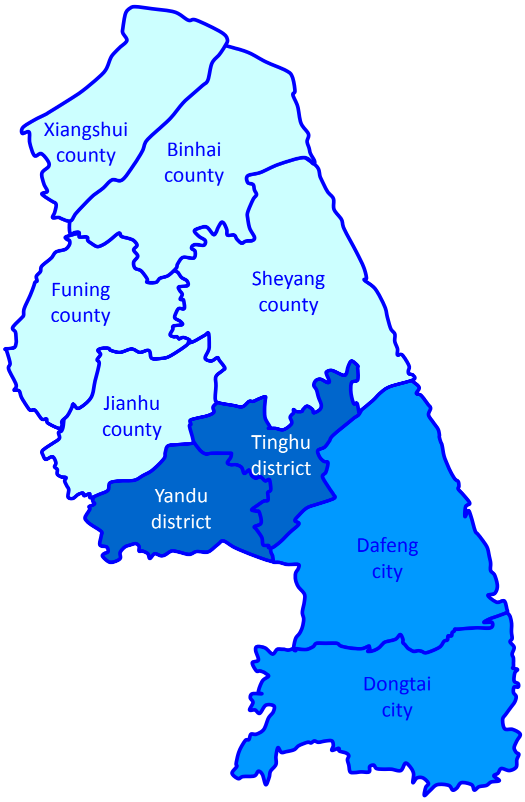

Table 1 shows that *Regions* include all seven types of county-level administrative divisions (listed in Table 1 from District to Adm. committee).[12] In terms of coverage, Region accounts for more than 98 percent of the total population in both 2000 and 2010.[13] As said, there were 338 regions in 2000 (334 prefectural levels and 4 municipalities) and 337 regions in 2010 (333 prefectural levels and 4 municipalities).

Agglomeration is a subset of *Region* excluding all 'rural' type counties. In particular, we only include District and County-level city. The share of the total population living in Agglomerations rose from about 46 per cent in 2000 to 52 per cent in 2010, partially because of direct migration and partially because of administrative changes.[14] By construction, *Agglomeration* is a cluster of urban areas that is viewed to operate as a consistent whole. Since it is a more coherent location definition than Region, the model discussed in section 2 should be more directly applicable at the Agglomeration level than at the Region level.

[12] There are four municipalities in China at the provincial level (Shanghai, Beijing, Tianjin, and Chongqing). These four are also classified as *Region*.

[13] Some county-level divisions are administrated by their provinces directly. In that case, the information of the divisions is excluded from the statistic of the prefectural levels. The population share of these county-level divisions is about 1.7 percent, which explains why coverage is not 100 percent of total population.

[14] Appendix B provides a sensitivity analysis with respect to administrative spatial changes.

City is a subset of Agglomeration consisting only of Districts. This more narrowly defined location thus excludes the County-level cities, which could be viewed as more or less independent satellites rather than a true part of the location itself. The share of the total population living in Cities rose from about 26 per cent in 2000 to 38 per cent in 2010, again partially because of direct migration decisions and partially because of changes in administrative division (as a consequence of migration). Since City is an even more coherent location definition than Agglomeration, the model discussed in section 2 should be most directly applicable at the City level.

As with all spatial analyses, administrative boundaries of spatial units (possibly) affect results. In our analysis it does not matter whether two administrative units are neighbors or far apart. If by coincidence an administrative border between two spatial units cuts through an agglomeration, this border-crossing agglomeration is not identified, because we make no distinction between neighbors and more distant spatial units. Our definition of Agglomeration, to some extent, corrects for this *within* prefectures, as Figure 2 illustrates for the prefecture Yancheng and the agglomeration consisting of Yandu, Tinghu, Dafeng, and Dongtai. In practice, this border effect implies that the larger the administrative unit the higher the probability that it encompasses an agglomeration within its borders.[15] On the other hand larger areas, such as our *Region* cover both urban and rural areas and explicitly add rural areas to the spatial unit. The choice of spatial units can thus interfere with the results. We report results at all spatial levels below in order to correct for potential biases that might be the result of spatial definitions. [16]

4.2 Skills

As is common in the literature, we use educational attainment as a proxy for skills. The Chinese census of population (2000 and 2010) categorizes six groups of educational attainments, related to the number of years of schooling. We aggregate the county-level educational data into the three types of locations and calculate the population share of each

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[15] This problem is also the reason why, for example, the Ellison and Glaeser (1997) index of localization increases with the size of the administrative spatial units (see Duranton and Overman, 2005). The Duranton-Overman (2005) index was developed to deal with this bias (see Briant et al., 2009 for further discussion of choosing spatial units).

[16] Also, different spatial scales could to some extent correct for the effects of selecting idiosyncratic years. Observations in 2010 might for example still be affected by the 2008 ‘Great Recession.’ Although we have no presumption that a reduction in economic growth rates affects a particular skill-group, whether it results in migration to or from cities, or whether it increases the informal sector, different spatial scales could capture these effects.

educational group in the total population of China, see Table 2.[17] Two observations are clear upon inspecting this table across time and location type.

Table 2: Population shares of skill group by educational attainment in 2000 and 2010 (%)

		Region		Agglomeration		City	
Education	years	2000	2010	2000	2010	2000	2010
Illiterate	0	8.0	4.9	6.3	3.6	5.8	3.2
Primary school	6	40.3	28.7	34.5	23.4	28.9	20.2
Middle school	9	38.7	41.8	40.4	40.6	40.1	38.1
High school	12	9.0	15.1	12.0	18.4	14.8	20.4
College	15	2.6	5.5	4.2	7.6	6.2	9.4
Bachelor	16+	1.4	4.0	2.6	6.5	4.3	8.7
Total % of spatial unit		100	100	100	100	100	100
As % of total population		84.1	88.7	39.9	47.5	22.3	31.9

Source: Chinese census of population 2000, 2010; *years* = number of years of schooling.

First, a comparison across time shows that the education level is *rising over time*: the population share is falling for the two lowest education levels and rising for the three highest education levels for all location types.[18] At the *Region* level the population share of illiterates falls, for example, from 8 percent to less than 5 percent and the population share of at least Bachelor rises from 1.4 to 4 percent.

Second, a comparison across location type shows that the education level is highest in *Cities* and lowest in *Regions*, with *Agglomerations* in between: the population share is falling for the three lowest education levels and rising for the three highest education levels as we move from Regions to Agglomerations to Cities in both time periods. In 2010, for example, the population share with Primary school falls from 28.7 percent at the Region level to 23.4 percent at the Agglomeration level to 20.2 percent at the City level. Similarly, the population share for College rises from 5.5 at the Region level to 7.6 at the Agglomeration level to 9.4 at the City level.

4.3 Sectors and occupations[19]

The distributions of sectors and occupations varies substantially across Chinese locations. In order to examine the interaction with population size we use data on the sector and

[17] In 2000, there were two additional educational groups, literacy class and technical school. We do not include them in this table since they are excluded in 2010. The data on educational attainment only includes the population of at least six years old persons.

[18] The third education level is rising for Regions, stable for Agglomeration, and falling for Cities.

[19] Occupations are determined by specific skills, training and qualifications for work. These can be put to use in various sectors. So different sectors can be home to the same occupation, and vice versa.

occupational employment from the Chinese census of population (2000 and 2010).[20] The sectors were classified into 15 categories in 2000 and expanded into 20 categories in 2010, while the number of occupations consists of 7 categories in both years.[21] To test the model we order sectors and occupations with respect to the corresponding skill intensities, which we collect from the China Labor Statistical Yearbook (2010). This lists sector and occupational employment as proportions of six educational attainments, measured by years of schooling.[22] The breakdown is provided both for the economy as a whole and for urban employment.[23]

Table 3: Average education of employment and population share in each sector

Sector	Average education						Share of working population spatial unit (%)					
	Total			Urban			Region		Agglomeration		City	
	Years	Order 2000	Order 2010	Years	Order 2000	Order 2010	2000	2010	2000	2010	2000	2010
Farming	7.38	1	1	7.73	1	1	64.5	41.4	46.7	25.7	32.5	17.3
Construction	9.03	2	2	9.54	2	2	2.7	4.8	4.0	5.2	4.7	5.3
Public Services	9.44	3	3	9.64	3	3	2.1	1.7	3.5	2.1	5.1	2.3
Mining	9.53	4	4	10.20	5	6	1.0	1.0	1.4	1.1	1.6	1.1
Hotel	9.55	-	5	9.76	-	4	na	2.4	na	2.9	na	3.4
Manufacturing	9.69	5	6	10.14	4	5	12.8	15.0	20.0	19.1	24.0	19.4
Trade	9.95	6	7	10.21	6	7	6.7	8.1	10.0	10.6	13.2	12.2
Transport	10.02	7	8	10.35	7	8	2.6	3.0	3.7	3.8	4.7	4.4
Public Utility	10.66	8	9	10.98	8	9	0.1	0.3	0.2	0.5	0.2	0.6
Real Estate	11.48	9	10	11.63	9	10	0.2	0.6	0.5	1.0	0.8	1.3
Utilities	11.72	10	11	12.06	10	11	0.6	0.6	0.9	0.8	1.2	0.9
Culture[24]	11.85	12	12	12.08	11	12	2.5	0.4	3.2	0.6	4.1	0.8
Business Serv.	12.04	-	13	12.30	-	13	na	14.1	na	18.1	na	20.7
Research	12.91	11	14	13.36	13	16	0.2	0.3	0.4	0.5	0.8	0.6
Computer	12.96	-	15	13.29	-	14	na	0.5	na	0.8	na	1.1
Public Health	13.00	13	16	13.35	12	15	1.1	1.0	1.5	1.3	2.0	1.5
Public Adm.	13.36	14	17	13.60	14	17	2.3	2.2	3.1	2.6	3.8	3.1
Banking	13.64	15	18	13.76	15	18	0.6	0.7	0.9	1.1	1.3	1.4
Education	14.09	-	19	14.36	-	19	na	2.0	na	2.3	na	2.7
As % of identified working population spatial unit							100	100	100	100	100	100
As % of total population							51.2	59.1	23.4	31.6	12.5	21.0

Sources: China Labor statistical yearbook (2010) and Chinese census of population (2010); years = the number of years of schooling; Serv. = Services; Adm. = Administration.

[20] The population of a location consists of both registered residents and non-registered residents living there continuously for at least five years.

[21] We drop the sector *International organizations* because it has almost zero employment.

[22] There is no educational information about sectors and occupations in 2000. Therefore, we order the skill intensity of sectors and occupations only based on the information available in 2010.

[23] Labeled ‘Total’ and ‘Urban’, respectively, in the left-hand panel of Table 3, see below.

[24] The sector *Culture* is a joint sector with *Education* in 2000. We use the average years of schooling of *Culture* and *Education* as the skill intensity of *Culture* in 2000, which are 12.97 years and 13.22 years for Total and Urban areas, respectively (see Table 3). The order of *Culture* in 2000 is based on this calculation.

The skill intensity is calculated as the weighted average years of schooling in each sector and occupation, ordered from low to high (see Tables 3 and 4, left-hand panels).[25] *Total* denotes the skill intensity of total employment, while *Urban* focuses on the employment in urban areas, which includes all districts in prefectural levels and the center of towns below county levels. Generally, the average years of education in urban areas are higher than that of the total areas. Most orders are identical in both Total and Urban levels with some exceptions. In the subsequent empirical tests, we use the Total order in Region estimations and the Urban order in Agglomeration and City estimations.

Table 4: Average education of employment and population share in each occupation

Occupation	Average education				Share of working population spatial unit (%)					
	Total		Urban		Region		Agglomeration		City	
	Years	Order	Years	Order	2000	2010	2000	2010	2000	2010
Agriculture	7.38	1	7.74	1	64.4	47.8	46.7	31.1	32.4	21.5
Production	9.29	2	9.68	2	16.0	22.9	24.0	28.3	28.0	29.3
Others	9.73	3	10.20	4	0.1	0.1	0.1	0.1	0.1	0.1
Business Serv.	9.82	4	10.07	3	9.2	16.3	13.8	21.9	18.0	25.8
Unit Head	11.72	5	12.12	5	1.7	1.8	2.5	2.6	3.4	3.2
Clerk	12.64	6	12.90	6	3.1	4.3	4.9	6.4	7.2	8.2
Technical Pers.	13.10	7	13.48	7	5.6	6.8	8.0	9.6	10.9	12.0
As % of identified working population spatial unit					100	100	100	100	100	100
As % of total population					51.3	51.1	23.5	26.2	12.6	16.9

Sources: China Labor statistical yearbook (2010) and Chinese census of population (2010); *years* = the number of years of schooling; Serv. = Services; Pers. = Personnel.

The right-hand panels of Tables 3 and 4 show the share of each sector and occupation in the total population of China for the three spatial units. For sectors (Table 3), Farming absorbed the largest share of population (except for Cities in 2010), followed by Manufacturing in both 2000 and 2010. Although it is hard to compare developments over time because of the identification of 4 new sectors, it is clear that the Farming employment fell drastically over time, namely from 65 to 41 percent at the Region level, from 47 to 26 percent at the Agglomeration level, and from 33 to 17 percent at the City level. A comparison across location types is simple for both periods: the working population share in Farming falls as we move from Region to Agglomeration to Cities, while the working population share for all other sectors either rises or is stable.

[25] Years of schooling=$\sum_{e=1}^{6} s_e * p_{ie}$, where *e* is the educational attainment, *i* denotes the sector or occupation, s_e denotes the years of schooling of each educational attainment, and p_{ie} denotes the share of the educational attainment *e* in the sector or occupation *i*.

For occupations (Table 4) the changes are straightforward (as there are no occupations added). The largest employment is in the occupation Agriculture (again, as with Farming for sectors, with the exception of Cities in 2010). The employment in Agriculture falls over time, while the employment in all other occupations rises over time for all location types (with the exception of Unit Heads in Cities). When we compare across location types, employment is falling for Agriculture and rising for all other occupations as we move from Region to Agglomeration to Cities in both periods (except for the 'Others' occupation, which is stable).

5 Empirical results

In this section, we use two empirical methods to test our hypotheses, namely, whether larger cities are relatively more skill abundant and whether larger cities house relatively more skill-intensive sectors or occupations. We also discuss if the strength of the hypotheses increases over time. We test this for the three spatial units described in the previous section. First, we examine the relationship between city size and the distribution of skills. We find that results strongly confirm the prediction of hypothesis 1 for all three location levels in both 2000 and 2010. We also find that the 2010 results are stronger than the 2000 results. Second, after investigating the distributions of skills, we examine the relationship between the city size and the distribution of sectors and occupations. We find clear evidence that China's sector and occupational distribution across cities changed from 2000 to 2010. More specifically, larger cities produced relatively more in higher skill-intensive sectors and occupations only in 2010. We do not find support for this prediction in 2000.

A remark on the locations included in the analysis and discussion of section 5 before we proceed is needed. Most provinces included in the China census are quite similar regarding location type, size, and population density structure, except for the four remote provinces Xinjiang, Tibet, Qinghai, and Inner Mongolia in the western and northern part of the country. As an illustration of this difference: the average county-level area size for these four provinces in 2010 is 15,100 km^2 or eight times larger than the 1,899 km^2 for the *other* provinces in China. As is customary for empirical research on China we therefore focus the analysis and discussion on the more similar other provinces throughout Section 5, excluding the four remote provinces. The robustness analysis in Appendix B briefly discusses the results if the four remote provinces are included.[26]

[26] Appendix B provides more details (under the heading 'paper' for the locations in the provinces analyzed in Section 5 and the heading 'all' if all locations in all provinces are included). Our selection thus largely coincides with locations east of the so-called Hu Line (from Heihe to Tengchong), except for Gansu and Ningxia.

5.1 Larger cities are relatively more skilled

A. Elasticity test

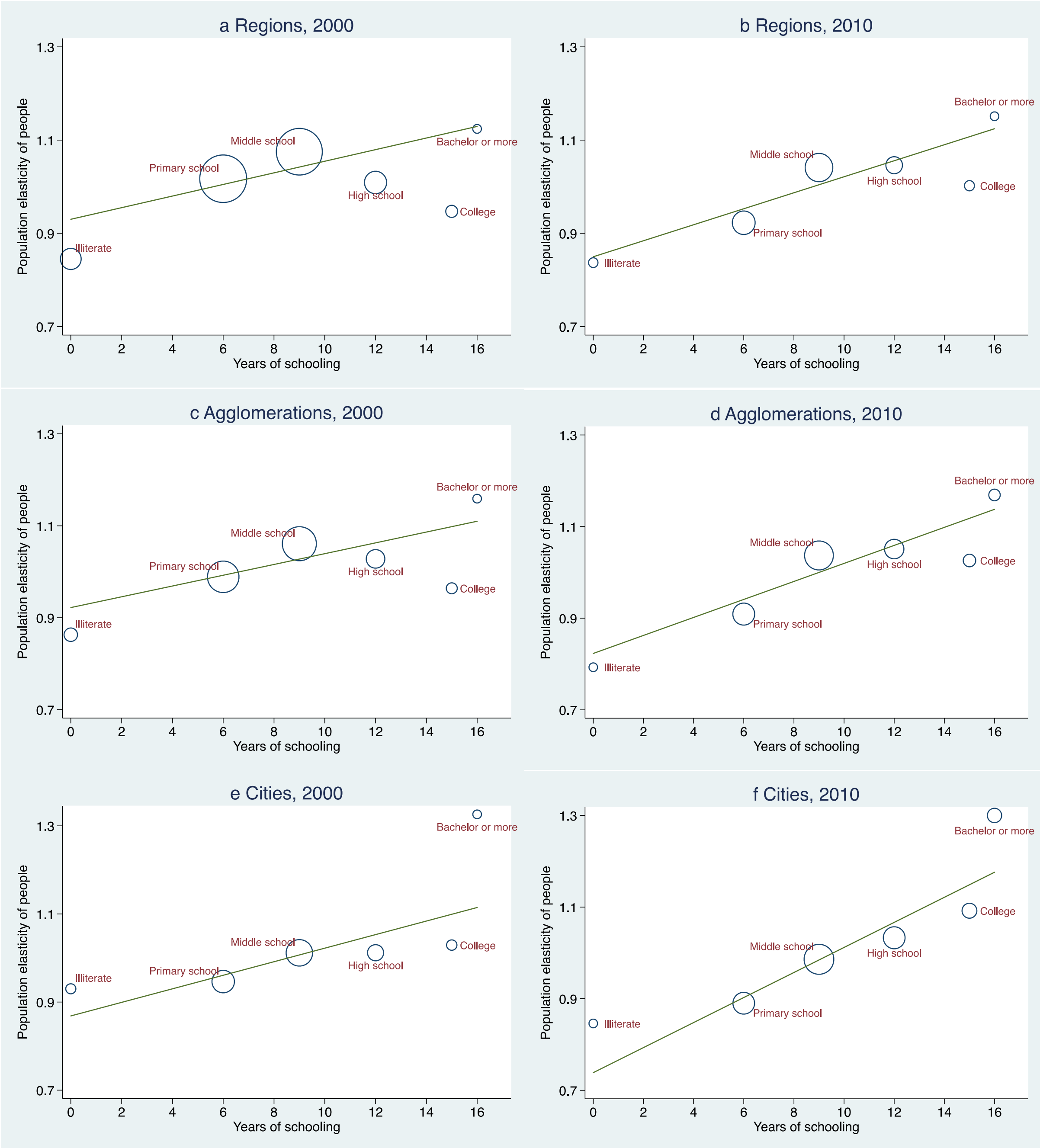
This subsection examines the links between city size and the distribution of skills. Table 5 reports the population elasticities, β_{v3} in equation (1), of educational groups for three types of location. In general, the estimated elasticities confirm that larger locations have relatively more skilled inhabitants: the elasticities are higher for more skilled educational groups at the *City* level in both years. Moreover, this trend is stronger in 2010 than in 2000. Similar results hold at the *Agglomeration* level and at the *Region* level, the only exceptions in 2010 are the coefficients for *College* and in 2000 for *Highschool* and *College*. To summarize, the elasticity test provides support for hypothesis 1: larger locations are relatively more skill abundant. This holds for both 2000 and 2010, but the results are stronger for 2010 than for 2000.

Table 5: Population elasticities of educational groups

Educational attainment	Region 2000	Region 2010	Agglomeration 2000	Agglomeration 2010	City 2000	City 2010
	(1)	(2)	(3)	(4)	(5)	(6)
Illiterate	0.845	0.837	0.863	0.793	0.930	0.846
	(0.049)	(0.057)	(0.031)	(0.033)	(0.035)	(0.039)
Primary school	1.017	0.923	0.988	0.909	0.946	0.890
	(0.022)	(0.029)	(0.019)	(0.020)	(0.023)	(0.022)
Middle school	1.075	1.041	1.061	1.038	1.012	0.986
	(0.026)	(0.021)	(0.015)	(0.015)	(0.010)	(0.010)
High school	1.009	1.046	1.028	1.051	1.012	1.033
	(0.046)	(0.030)	(0.023)	(0.015)	(0.028)	(0.016)
College	0.947	1.002	0.964	1.027	1.029	1.092
	(0.049)	(0.039)	(0.034)	(0.028)	(0.038)	(0.026)
Bachelor or more	1.124	1.151	1.159	1.169	1.326	1.300
	(0.080)	(0.064)	(0.054)	(0.046)	(0.054)	(0.041)
Observations	1,776	1,776	1,692	1,722	1,506	1,626
R-squared	0.909	0.893	0.911	0.911	0.889	0.899
Education FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: standard errors in parentheses, clustered by relevant spatial unit; shaded cells indicate falling rather than rising elasticities going down the respective row

Figure 3: Population elasticities of skills measured by years of schooling



Note: The size of the bubble measures the size of each educational level; The fitted lines are weighted by population shares; The vertical axis does not start at zero.

To illustrate our findings we graph the population elasticities of the six educational groups listed in Figure 3 relative to the corresponding educational levels in both years in Figure 3. We do this for all three location levels in a bubble diagram, where the size of the bubble is proportional to the population share of that education level. It is clear that educational levels *Middle school* and *Primary school* account for the largest proportion of the total population at the *Region* level in 2000, while the composition of educational attainment is more balanced at the *City* level in the same year. The *Agglomeration* level is intermediate of these two extremes. This implies that the areas with more urban features are more skill abundant. The educational composition was more balanced in 2010 for all three location levels (with middle school as the largest group), implying that the gap between rural and urban areas was getting smaller in this time period. The diagrams also display a regression line (weighted by population shares) for the estimated elasticities relative to the years of schooling. The bubbles get closer to the fitted line over time, and the slopes of the fitted lines are steeper in 2010, especially for *Agglomeration* and *City*. It is worth noting that the elasticities for *Bachelor or more* are positive outliers at the *City* level in both years, implying that people with the highest education levels choose to live in larger cities.

Table 6: Hypothesis 1 elasticity test: large locations are more education-skill intensive

a Weak test
Rejection if the elasticity of a higher skill level is significantly lower than of a lower skill level

		Region		Agglomeration		City	
Year	Pairs	# Reject	Percent	# Reject	Percent	# Reject	Percent
2000	15	3	20	2	13	0	0
2010	15	0	0	0	0	0	0

b Strong test
Confirmation if the elasticity of a higher skill level is significantly higher than of a lower skill level

		Region		Agglomeration		City	
Year	Pairs	# Confirm	Percent	# Confirm	Percent	# Confirm	Percent
2000	15	5	33	9	60	7	47
2010	15	9	60	12	80	14	93

The null hypothesis is that any two elasticity estimates are equal; the test used is two-sided at 5% significance; see the main text for details.

Table 6 provides a summary of the hypothesis that the estimated elasticities rise with higher education levels. We distinguish between two types of tests.

Table 6a portrays the results of what we call a *weak test*, where we conclude that the hypothesis is rejected if the elasticity of a higher skill level is *significantly lower* than of a lower skill level (at the 5 percent level). Note that we can compare the elasticities of six education levels in $6 \times \frac{5}{2} = 15$ different ways. The table reports both the number of rejections and the percent of rejections. This test performs excellent for cities (with no rejections at all) and for the year 2010 (again with zero rejections). It is reasonable for agglomerations and regions in 2000, with 13 and 20 percent rejections respectively.

Table 6b portrays the results of what we call a *strong test*, where we conclude that the hypothesis is confirmed if the elasticity of a higher skill level is *significantly higher* than of a lower skill level (at the 5 percent level). The table reports both the number of confirmations and the percent of confirmations. This test performs well for regions, agglomerations, and cities in the year 2010, with 60, 80, and 93 percent confirmations respectively. It performs reasonably well, but at a lower level, in the year 2000, with 33, 60, and 47 percent confirmations respectively.

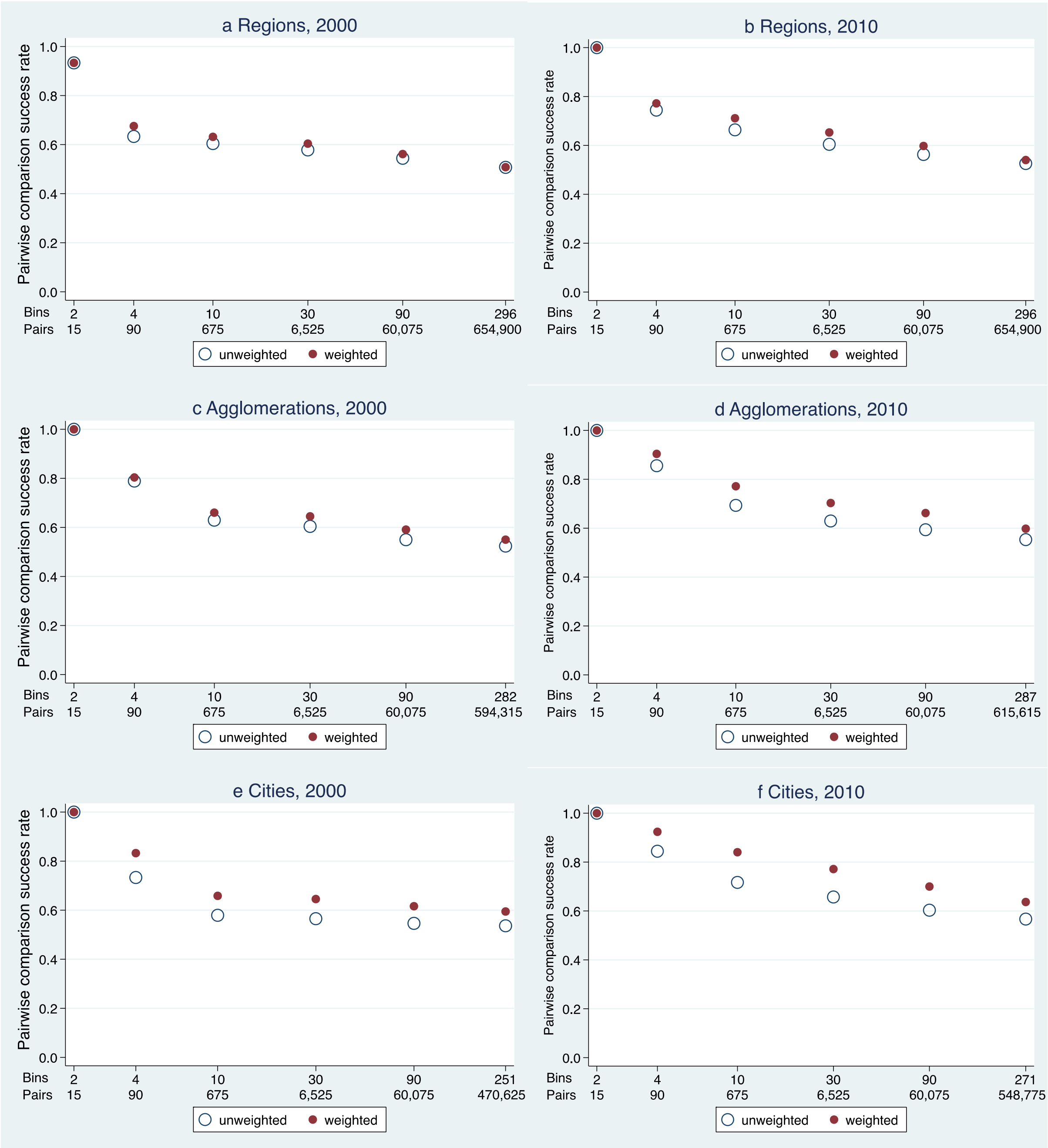
Taken together we conclude from Table 6 that the elasticity tests perform better in 2010 than in 2000 and that they improve if we move from regions to agglomerations to cities.

B. Pairwise comparison test

Next, we focus on the pairwise comparison test regarding the relationship between location size and skill abundance. As explained in the previous section, by examining 'bins' of ordered groups of cities, the pairwise comparison test examines whether the relatively more skilled population is to be found in relatively large locations. Since we analyze 2, 4, 10, 30, and 90 bins as well as 296 individual locations for 6 different skill categories, we make 722,280 bilateral comparisons for each location type for each year. The results are summarized in Figure 4 both regarding the unweighted and weighted success rate of the pairwise comparison tests (consisting in total of about 4.3 million bilateral comparisons, see Table A7 for details).

Consistent with the hypothesis, the success rates of these comparisons are higher in 2010 than in 2000 for all three types of locations. As with the elasticities test, the geographic differences are clear. The success rate is highest for *City*, followed by *Agglomeration*, followed by *Region*. Restricting attention to the cities improves results considerably. It is also clear that the success rate of the pairwise comparison tests improves if we lump cities together in bigger groups (and thus a lower number of bins). The smallest groups of individual cities have a weighted success rate ranging from a minimum of 50 percent (for *Regions* in 2000) to above 60 percent (for *Cities* in 2010). In contrast, the success rate when we have only two bins (containing half of the sample per bin) is 100 percent (with the exception of *Regions* in 2000). The weighted success rates are higher than the unweighted ones, indicating that the comparison test is more likely to hold if the difference in the size of the populations of the compared locations is big. Note that the gap between the weighted and unweighted results is largest for *City* and smallest for *Region*.

Figure 4: Pairwise comparison of six educational attainment levels



Our findings above suggest that the theoretical model works quite well regarding the relationship between location size and skill abundance. The tests perform better as we go from the *Region* level to the *Agglomeration* level, and from the *Agglomeration* level to the *City* level. This suggests that the model is more appropriate if the locational scale is more precisely and more coherently defined. In addition, the tests perform better in 2010 than in

2000. We take this as an indication of China's move over time to a more market-oriented economy allowing for greater labor mobility.[27]

5.2 Larger cities specialize in high skill-intensive sectors and occupations

In this subsection, we tests whether larger cities are more specialized in high skill-intensive sectors and occupations in 2000 and 2010. First, we estimate the sectoral and occupational population elasticities for the elasticity test. Second, we use the pairwise comparisons test to identify the spatial patterns of sectoral and occupational employment.

A. Elasticity test-sectors

We start with the elasticity test for sectoral employment. As mentioned in subsection 4.3, the population elasticities at the *Region* level are based on the Total skill intensities, while the population elasticities at the *Agglomeration* and *City* levels are based on the Urban skill intensities. Figure 5 plots the 15 and 19 sectoral population elasticities against their corresponding skill intensities in 2000 and 2010. In general, the sectoral composition, measured by the size of the bubbles, shows a diversified pattern among the three location levels. *Farming* dominates at the *Region* level, particularly in 2000, while *Manufacturing* becomes more important for the urban areas, also over time.[28] Also note that the sector *Business Services*, which was absent in the sectoral categories in 2000, accounts for the largest proportion of total employment at the *City* level in 2010.

The elasticity test for sectors performs badly in 2000. The fitted line is basically horizontal for *Agglomeration* and *City*, while it even has a negative slope for *Region* (see Figure 5a). The dominant high estimated elasticity for *Farming* at the *Region* level is the main culprit, indicating that large rural areas with a big population also have a lot of farming. For the urban areas *Real Estate* and *Research* have high elasticities, while *Mining*, *Public Utilities*, *Utilities*, *Public Health*, *Public Administration*, and *Banking* have low elasticities relative to the average schooling levels. The elasticity test for sectors improves by 2010. All fitted lines have a positive slope, indicating that in 2010 large locations produce relatively more in skill-intensive sectors (see Figure 5b, 5d, 5f). The estimated elasticity for low-skilled *Farming* falls considerably for all location types, particularly for *Cities*. Perhaps this reflects the decline of hidden unemployment in rural areas.

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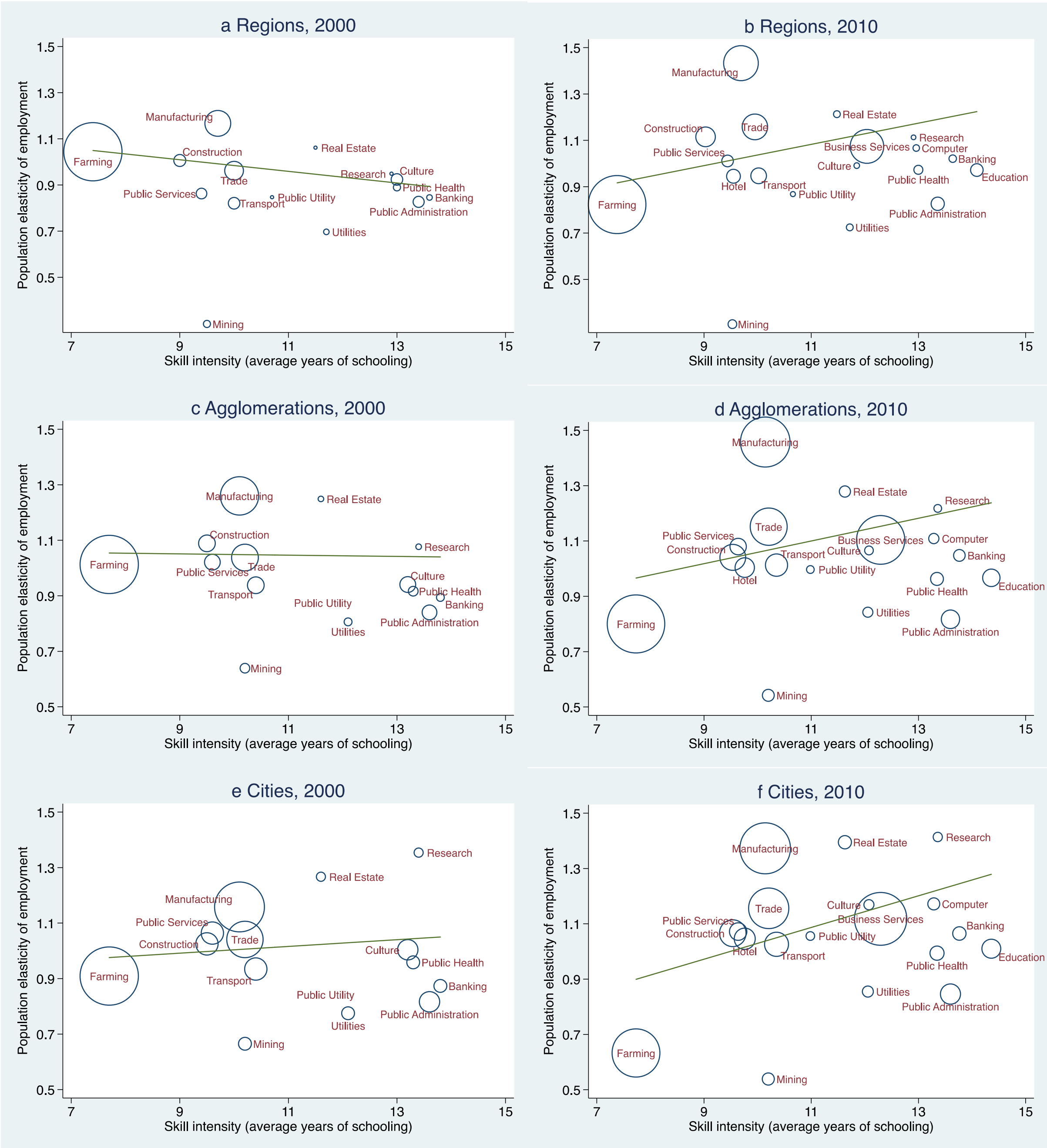
[27] Similar, but somewhat weaker, results hold when we analyze all locations (including the remote provinces Xinjiang, Tibet, Qinghai, and Inner Mongolia), see Appendix B.

[28] This is consistent with the findings of Brakman et al. (2014), who find that localization of firms increase over time, suggesting that firms increasingly benefit from agglomeration economies in cities.

Figure 5: Sectors' population elasticities and skill intensities



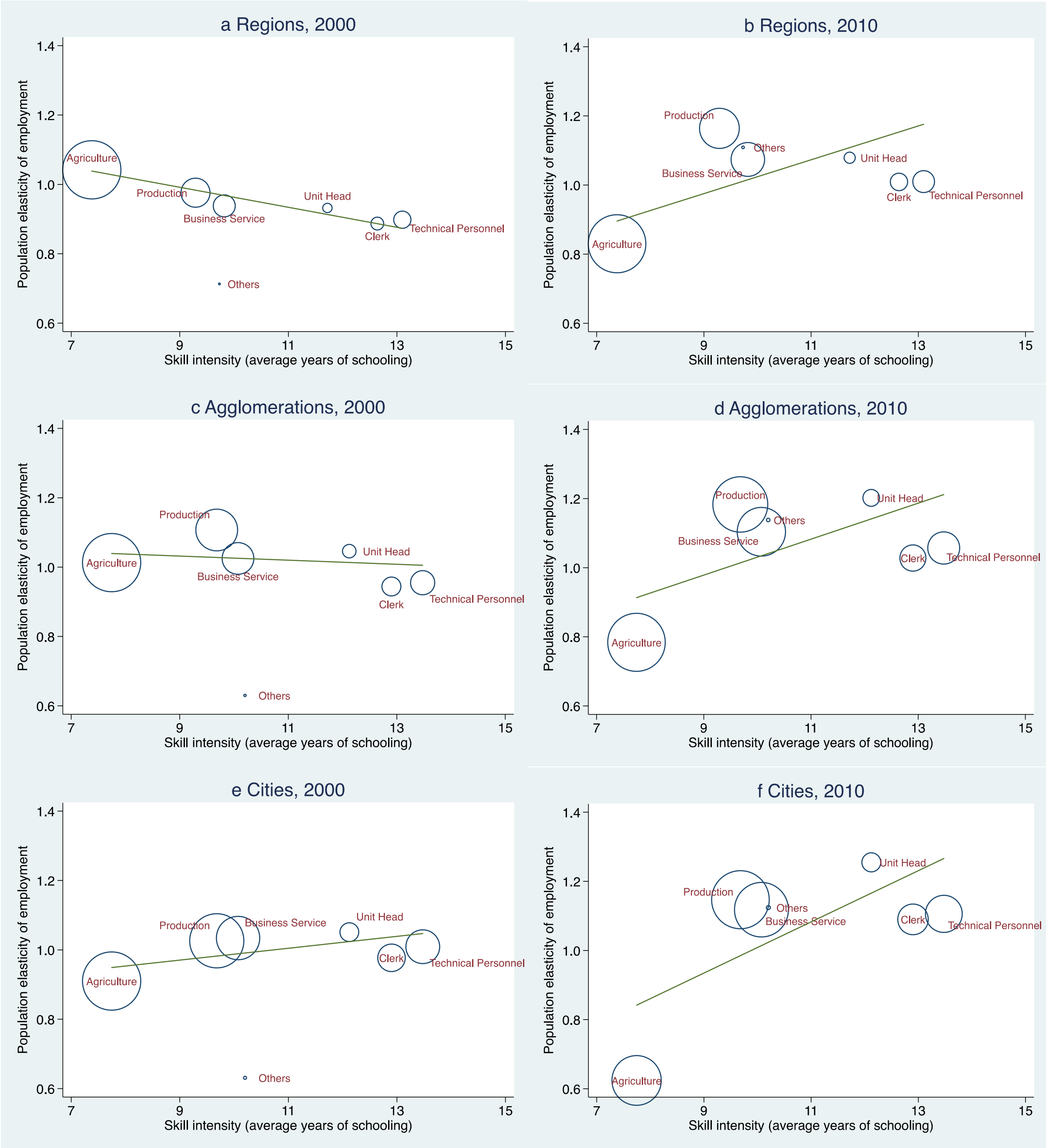
Note: The size of the bubble measures the size of sectors. The fitted lines are weighted by population shares. The vertical axis does not start at zero.

A summary of the formal tests of the comparison of the various estimated elasticities is reported in Table 7 below, which again distinguishes between the weak test and the strong test and reports the number of rejections and confirmations, as well as their percentages. Since there are 15 sectors in 2000 and 19 in 2010 we have 105 elasticity comparisons in 2000 and 171 in 2010. The number of rejections of the weak test is considerable in all cases, ranging from 36 to 49 percent and there is no improvement over time. The number of confirmations of the strong test is modest ranging from 22 to 44 percent, although there is some improvement as we go from 2000 to 2010 for all location types. Also note that the highest scoring confirmation at the sector level is for cities in 2010 (44 percent), which at the same time has a substantial number of rejections as well (36 percent). Based on these summary tests, one would be tempted to conclude that the sectoral composition of skills is too diversified to result in clear sorting of high-skilled sectors in bigger locations.

B. Elasticity test-occupations

In this subsection, we use the elasticity test to examine whether large locations specialize in relatively high-skilled occupations. Our data identifies only seven occupational categories. The estimated population elasticities are plotted in Figure 6 relative to the average number of years of schooling in 2000 and 2010 for the three location levels, with the size of the bubbles proportional to the number of people working in a particular occupation. As with the sector analysis, *Agriculture* takes up a dominant position in size, particularly at the *Region* level and mainly in 2000. The share of employment in *Production* and *Business Services* increased substantially over time (they became the two largest occupation categories in 2010 at the urban levels). As with the sector analysis, the slope of the fitted lines for the elasticities of occupations is basically horizontal in 2000 for *Agglomeration* and even negative for *Regions*. As with the sector analysis, the predictions perform better in 2010 with fitted lines with a positive slope for all three location types. Again similar to the sector analysis, the estimated elasticity of *Agriculture* as an occupation declined substantially in 2010. In contrast to the sector analysis, however, a visual inspection suggests that the overall performance of the elasticity test seems to be quite acceptable by 2010, which is confirmed by the formal analysis discussed below.

Figure 6: Occupations' population elasticities and skill intensities



Note: The size of the bubble measures the size of occupations.The fitted lines are weighted by population shares. The vertical axis does not start at zero.

The occupational part of Table 7 shows the summary of the formal elasticity tests, again for the weak test and the strong test. Since there are 7 occupations in both years the number of bilateral comparisons is 21. The number of rejections of the weak test ranges from 10 to 52 percent. The performance improves over time for agglomerations and cities, but not for regions. It is reasonable at the city level, but not at the agglomeration or region level. The number of confirmations of the strong test ranges from 5 to 38 percent. The performance improves over time for all location types and is reasonably high at the agglomeration and city level by 2010 (namely 33 and 38 percent, respectively). All in all, on the basis of Table 7, we conclude that the sorting of high-skill occupations in bigger locations is more or less confirmed at the city level (certainly by 2010), but not impressive for either regions or agglomerations.

Table 7: Hypothesis 2 elasticity test: large locations have more skill intensive sectors/occupations

a Weak test
Rejection if the elasticity of a higher skill level is significantly lower than of a lower skill level

			Region		Agglomeration		City	
	Year	Pairs	# Reject	Percent	# Reject	Percent	# Reject	Percent
Sector	2000	105	38	36	51	49	43	41
	2010	171	63	37	70	41	62	36
Occupation	2000	21	4	19	11	52	5	24
	2010	21	8	38	7	33	2	10

b Strong test
Confirmation if the elasticity of a higher skill level is significantly higher than of a lower skill level

			Region		Agglomeration		City	
	Year	Pairs	# Confirm	Percent	# Confirm	Percent	# Confirm	Percent
Sector	2000	105	23	22	24	23	32	30
	2010	171	57	33	67	39	75	44
Occupation	2000	21	1	5	3	14	3	14
	2010	21	2	10	7	33	8	38

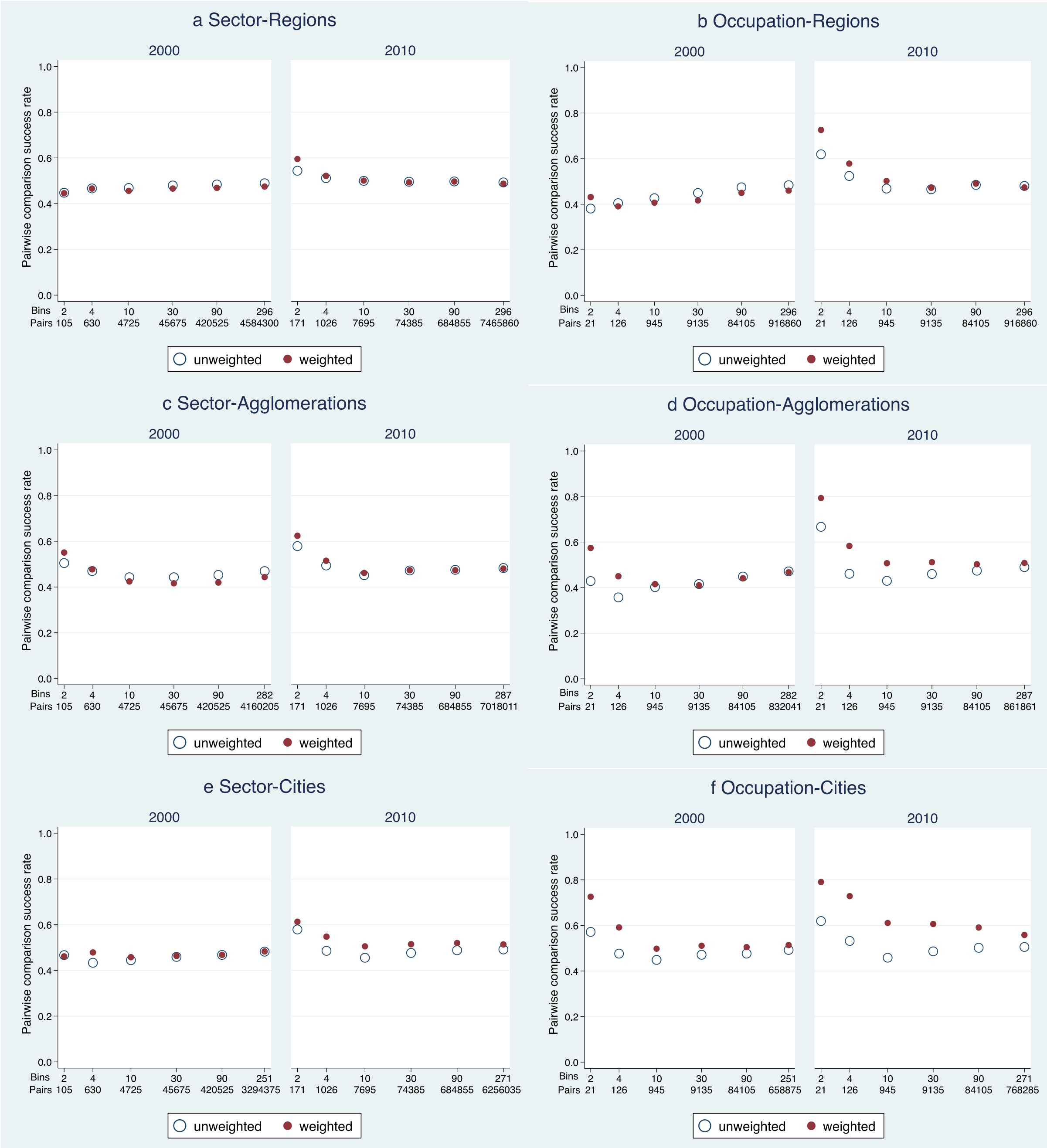
The null hypothesis is that any two elasticity estimates are equal; the test used is two-sided at 5% significance; see the main text for details.

C. Pairwise comparison test

We next turn to the results of the pairwise comparison test for sectors and occupations (see Figure 7 and also Appendix B). Since we have 7 different occupation categories, each figure for a given location level and year for occupations is based on about 1 million bilateral comparisons. Since we have 15 sectors in 2000 and 19 sectors in 2010, each figure for a given location level and year for sectors is based on about 5 million bilateral comparisons in 2000 and 8.2 million bilateral comparisons in 2010. In total, Table 7 is thus based on about 46 million bilateral comparisons, both weighted and unweighted.

At the *sector* level, the success rate of the bilateral comparisons improves from 2000 to 2010 for all three types of locations. This holds in particular for the weighted values of the comparison of larger groups of cities (the lower bin numbers). Nonetheless, even for those groups the success rate remains small in 2010, only around 60 percent. The majority of the comparisons (either weighted or unweighted) is close to the 50 percent benchmark.

Figure 7: Pairwise comparison of 19 (15) sectors and 7 occupations



At the *occupation* level, the success rate of the bilateral comparisons also improves from 2000 to 2010. This time, however, the improvement is more substantial. This holds in particular for the weighted success rates, for the larger groups of cities comparisons (success rates of 80 percent for the lower bin numbers), and for the *City* level. This confirms our earlier analysis that performance improves over time, is better for more consistently defined locations, and that the model is more appropriate for occupations than for sectors.

To summarize, we find some evidence that larger *cities* in China have become relatively more specialized in skill-intensive sectors and occupations over the past decade. This change may be indicative of the more market-oriented economic development accompanied by more labour mobility and rapid urbanization from 2000 to 2010. The degree of urbanization in China in 2000 was only about 37 percent, indicating that about two-thirds of the population still lived in rural areas and relied primarily on farming.[29] Since *Region* and *Agglomeration* in China include not only urban areas but also rural areas and agricultural activities belong to low skill-intensive economies, the estimated results do not confirm our predictions in *Region* and *Agglomeration* in 2000, for both sectors and occupations. In contrast, the degree of urbanization has increased to about 50 percent in 2010. The move to a more market-oriented economy based on manufacturing and business services attracted a large number of workers from rural into urban areas. This transition is illustrated by the improvement in predictive power over time of the model as tested in this section. Our conclusions are not affected by sensitivity tests related to definitions of spatial units, sectors, or the inclusion of peripheral spatial units.[30]

6 Conclusions

The traditional literature on China indicates that the concentration of economic activities is lower in China than in other industrialized countries. Institutional limits to internal migration , notably the Hukou system, are largely held responsible for this finding; due to this system firms and workers are not able to maximize the benefits from agglomeration economies. China is, however, rapidly changing. Urbanization is surging and millions of new jobs are created in urban areas.

Dense areas and big cities are more productive than smaller cities and the question arises whether also in China, like in other countries, more productive workers and firms sort into bigger cities. This is the main question of this paper. We empirically test the theoretical framework of Davis and Dingel (2013) which predicts that there is relative sorting of high-skilled workers in larger cities. Associated with this process there is also a relative sorting of

[29] The data of urbanization is calculated from the Chinese census of population. Urbanization is defined as the share of the population living in all districts and the center of towns below county levels in total population.
[30] Appendix B gives information on the sensitivity tests.

high-skilled occupations and skill-intensive sectors in larger cities. As the Hukou system is becoming more liberal we expect that this sorting process becomes more prominent over time.

Our analysis is based on two types of tests, namely a population elasticity test and a pairwise comparison test. We do this for three types of Chinese locations (regions, agglomerations, and cities) and for three types of observables (skills, occupations, and sectors) in 2000 and 2010. The elasticity test holds if the estimated population elasticity is higher for higher skills (or for more skill-intensive occupations or sectors). The pairwise comparison test holds if the largest (group of) location(s) is relatively skill abundant (or skill-intensive occupation or sector abundant) if we compare two (groups of) cities. In all cases, the results found by the elasticity test are in line with the results found by the pairwise comparison test. Our main findings can be summarized as follows.

- The predictive power of the sorting model is highest for cities, followed by agglomerations and regions, respectively.
- The predictive power of the sorting model is highest for skills, followed by occupations and sectors, respectively.
- The predictive power of the sorting model improves over time.

We view our results as an indication that China's economy is transforming into a more market-oriented economy which not only allows for more labor mobility over time, but also allows China to benefit increasingly from agglomeration economies. Our results also indicate that care should be given regarding the type of location (the level of aggregation). In particular, the sorting model works best when comparing rather precisely defined and coherent locations (cities) rather than more heterogeneous areas (regions). Furthermore the results indicate that the sorting model works best when skill levels are measured as directly as possible, which explains the ranking for (education) skills, occupations, and sectors.

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Appendix A Description of Sectors and Occupations

Table A1: Full name and short name of sector and occupation

A. Sector		
Short name	Full name-2000	Full name-2010
Farming	Farming, Forestry, Animal Husbandry and Fishery	Farming, Forestry, Animal Husbandry and Fishery
Construction	Construction	Construction
Public Services	Social Service	Personal and other Services
Mining	Mining and Quarrying	Mining and Quarrying
Hotel	-	Hotel and Catering Services
Manufacturing	Manufacturing	Manufacturing
Trade	Wholesale and Retail Trade & Catering Services	Wholesale and Retail Trade
Transport	Transport, Storage, Post & Telecommunications	Transport, Storage, Post & Telecommunications
Public Utility	Geological Prospecting & Water Conservancy	Water Conservancy, Environment and public Utility Management
Real Estate	Real Estate Trade	Real Estate
Utilities	Production and Supply of Electricity Gas and Water	Production and Supply of Electricity Gas and Water
Culture	Education, Culture and Art, Radio Film and Television	Culture Sports and Entertainment
Business Services	-	Leasing and Business Services
Research	Scientific Research and Poly-technical Services	Scientific Research, Technical Services & Geological Prospecting
Computer	-	Data Transmission Computer Service & Software
Public Health	Health Care, Sporting and Social Welfare	Public Health Social Securities & Social Welfare
Public Administration	Government Agencies, Party Agencies and Social Organizations	Public Administration and Social Organizations
Banking	Finance and Insurance	Banking
Education	-	Education

B. Occupation		
Short names	Full name-2000	Full name-2010
Agriculture	Agriculture and Water Conservancy Laborers	Agriculture and Water Conservancy Laborers
Production	Production, Transport Equipment Operators and Related Workers	Production, Transport Equipment Operators and Related Workers
Others	Others	Others
Business Service	Business Service Personnel	Business Service Personnel
Unit Head	Unit Head	Unit Head
Clerk	Clerk and Related Workers	Clerk and Related Workers
Technical Personnel	Professional and Technical Personnel	Professional and Technical Personnel

Appendix B Sensitivity

Appendix B provides a range of sensitivity tests.

Inclusion of the remote provinces

Table A2 provides the educational population elasticities if all Chinese regions are included in the analysis, that is including the four remote provinces Xinjiang, Tibet, Qinghai, and Inner Mongolia. It is thus the equivalent of Table 5 in the paper and the results are quite similar. They are graphed in Figure A1, which is similar to Figure 2 in the paper. For ease of reference, Figure A2 then directly compares the results of the weighted pairwise comparisons reported in the paper (referred to as 'paper') with the weighted pairwise comparisons if all locations are included (referred to as 'all locations'; this figure is the counterpart to Figure 3). It is immediately clear that the results are quite similar (but slightly weaker, as is to be expected) to those reported in the paper. Tables A3-A6 provide the population elasticity estimates for sectors (A3 and A4) and occupations (A5 and A6) for 2000 (A3 and A5) and 2010 (A4 and A6). To ease comparison with the results in the paper these are directly listed in the tables as well. In all cases the results are quite similar to those in the paper, as is graphically illustrated in Figures A3 and A4 (which are the equivalent of Figures 5 and 6 in the paper). Tables A7-A9 report the results of the pairwise comparisons, both for all locations and the paper. Figure A5 then directly compares the results of the weighted pairwise comparisons reported in the paper with the weighted pairwise comparisons if all locations are included for sectors and regions (this figure is the counterpart to Figure 7). It shows that these results for sectors and occupations are weaker for all locations for regions and agglomeration and about similar for cities. To round of this discussion, Table A10 compares the slopes of the regression lines in Figures 3, 5, and 6 of the paper and compares with the slopes of the regression lines in Figures A1, A3, and A4 of the Appendix. None of the reported slopes are significantly different at the 5 percent level.

Change of location type definition

As discussed in the paper we identify regions, agglomerations, and cities by county-level location type in 2000 and 2010. When there is a change in the number of people living in a certain (aggregate) location type it can thus be the result of either an increase in population in the county of that type or because the county was redefined in 2010 relative to what it was in 2000.[31] Note that such a redefinition may be entirely appropriate from an economic

[31] See for a detailed discussion of these issues, Baum-Snow et al., (2013).

perspective if a county changes from a more rural setting to a more urban setting. Nonetheless, to analyze if our results are driven by the redefinition of location type in 2010 relative to 2000 we also analyze the sorting of education, sectors, and occupations in 2010 using as much as possible the county level definition of 2000. Taken together, 70 out of 2523 county level locations of 2010 changed from 2000.[32] Figure A6 provides the population elasticities and the pairwise comparison for education level in 2010 with the county level definition as much as possible equal to that in 2000. Figure A7 provides the population elasticities for sectors and occupations, while Figure A8 provides the pairwise comparison for sectors and occupations, after correcting for location type changes (referred to as 'same locations'). In all cases the results are quite similar if we control for changes in location type definition. To conclude this discussion, Table A11 compares the slopes of the regression lines for 2010 in Figures 3, 5, and 6 of the paper with the slopes of the regression lines in Figures A6 and A7 of the Appendix. None of the slopes is significantly different.

Change in the number of sectors

As summarized in Table A1, we can identify 15 sectors in 2000 and the same 15 sectors plus 4 additional sectors (for a total of 19 sectors) in 2010. To analyze the extent to which our sector results in 2010 are based on the inclusion of four additional sectors, we therefore report in Figure A9 the population elasticities and the pairwise comparison for 2010 if we restrict attention to the same sectors identified in 2000. Again the results are quite similar. To round of this discussion, Table A12 compares the slopes of the regression lines for 2010 in Figure 5 of the paper with the slopes of the regression lines in Figure A9 of the Appendix. None of the slopes is statistically different.

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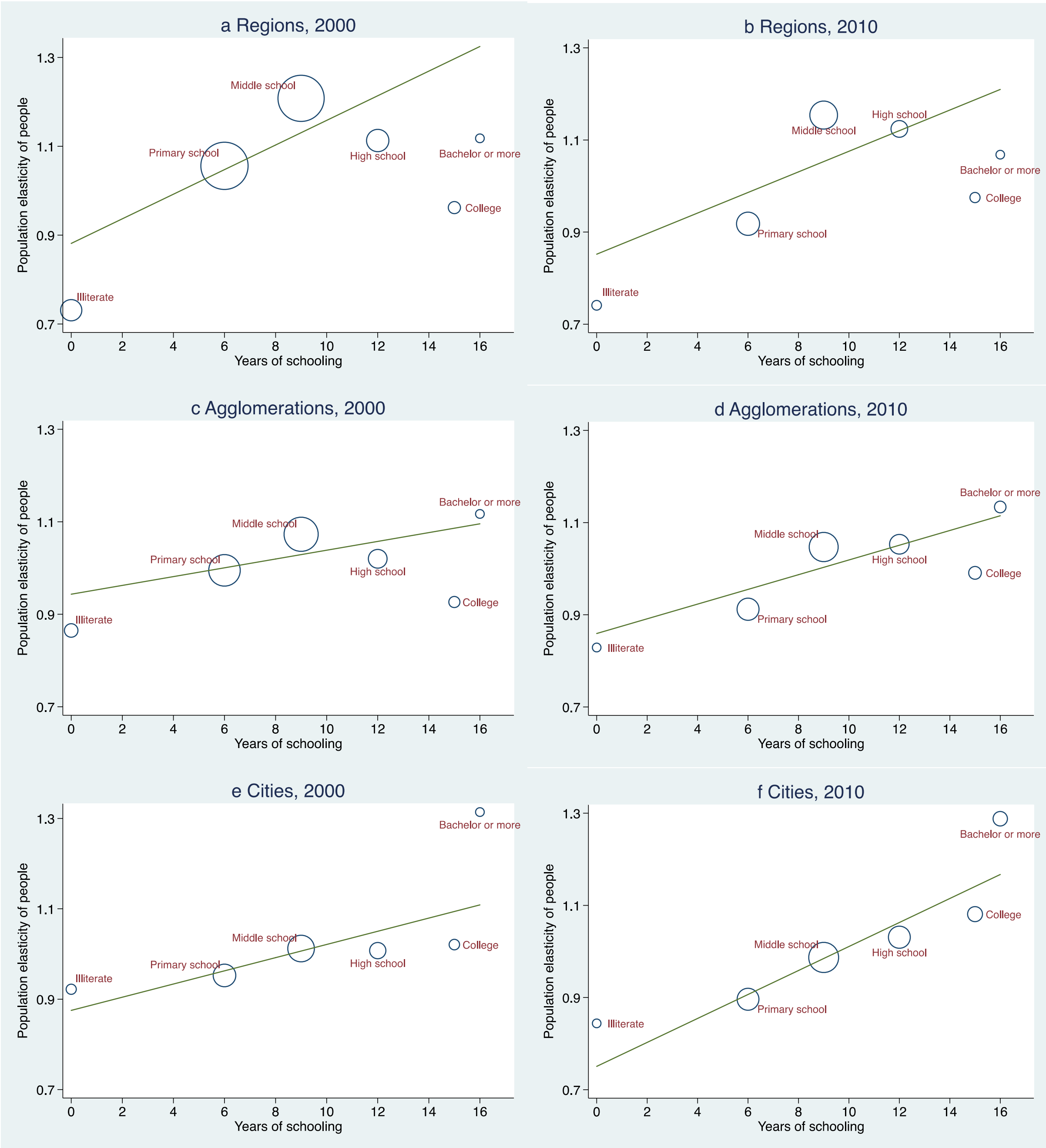
[32] Some difficulties arise in matching location type. For example, original locations A and B in 2000 split into C, D, and E over the past decade and hence we observe C, D, and E instead of A and B in 2010. There are two situations. First, if A and B were of the same location type (e.g. county) in 2000, we keep C, D and E consistent with their original type (county). However, if A and B used to belong to different location types, we leave the locations C, D and E unchanged (i.e., current location type, independent of the original type). There are only 7 transitions of the latter case in the sample. There were 2531 county level locations in 2000. The number of changes is counted based on the location in 2010. Some location changes are not one-to-one. For example: (1) county A (2000) + county B (2000) = district C (2010) implies one change was counted, (2) district A (2000) = district B (2010) + district C (2010) implies no change was counted, (3) county A (2000) = district B (2010) + district C (2010) implies two changes were counted, and (4) county A (2000) + district B (2000) = county C (2010) + district D (2010) + district E (2010) implies no change was counted.

Table A2: Population elasticities of educational groups, all locations (incl. remote regions)

Educational attainment	Region		Agglomeration		City	
	2000	2010	2000	2010	2000	2010
	(1)	(2)	(3)	(4)	(5)	(6)
Illiterate	0.731	0.741	0.865	0.829	0.922	0.844
	(0.046)	(0.054)	(0.028)	(0.034)	(0.034)	(0.038)
Primary school	1.056	0.918	0.995	0.912	0.953	0.896
	(0.018)	(0.021)	(0.017)	(0.017)	(0.022)	(0.022)
Middle school	1.208	1.154	1.073	1.047	1.013	0.987
	(0.038)	(0.029)	(0.015)	(0.014)	(0.010)	(0.011)
High school	1.113	1.125	1.020	1.053	1.008	1.031
	(0.049)	(0.034)	(0.022)	(0.014)	(0.027)	(0.015)
College	0.962	0.975	0.927	0.991	1.021	1.081
	(0.044)	(0.032)	(0.032)	(0.025)	(0.037)	(0.026)
Bachelor or more	1.118	1.068	1.117	1.133	1.314	1.288
	(0.058)	(0.047)	(0.048)	(0.040)	(0.053)	(0.041)
Observations	2,028	2,022	1,872	1,896	1,572	1,704
R-squared	0.907	0.893	0.913	0.912	0.889	0.899
Education FE	Yes	Yes	Yes	Yes	Yes	Yes

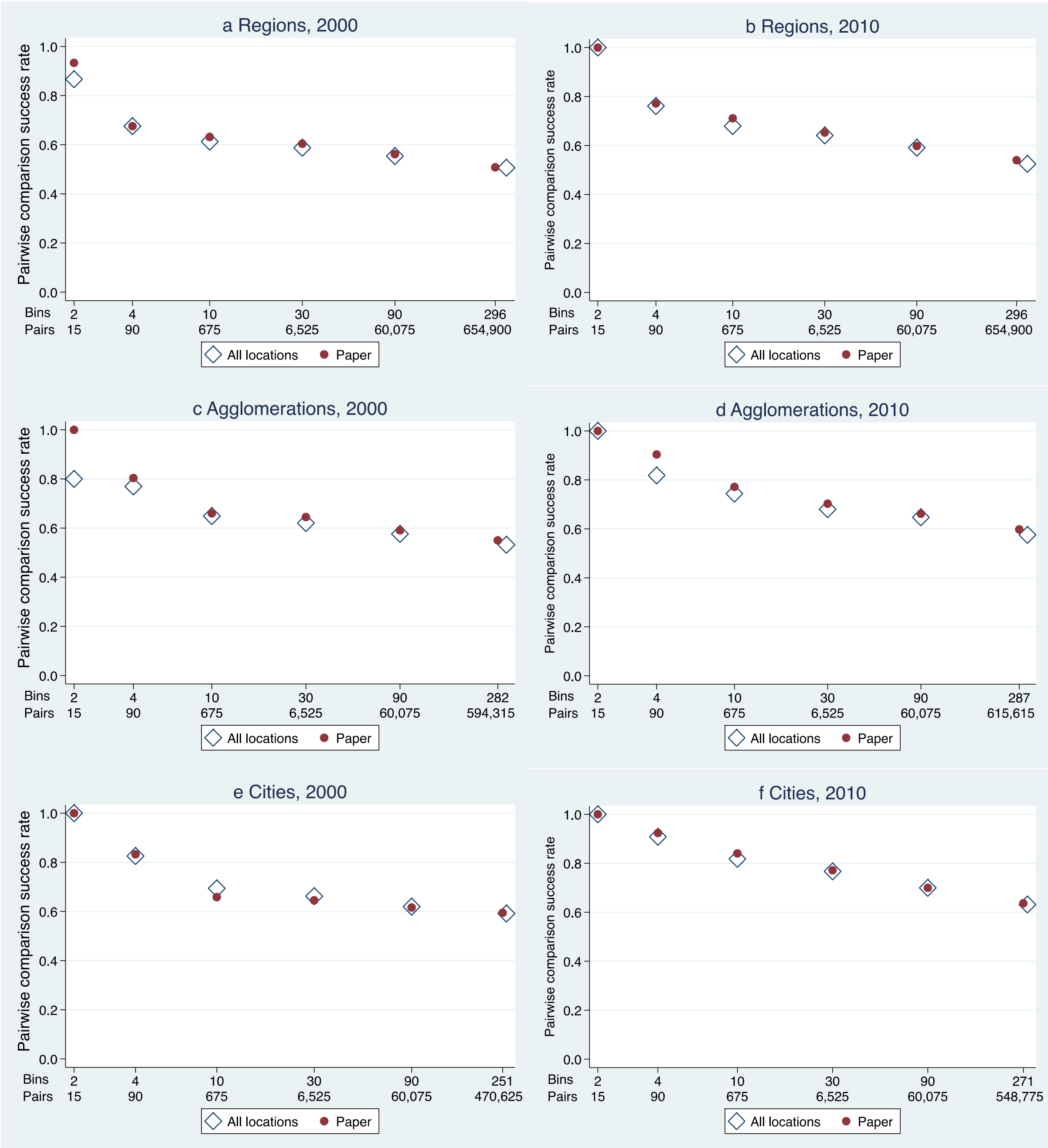
Note: standard errors in parentheses, clustered by relevant spatial unit; shaded cells indicate falling rather than rising elasticities going down the respective row

Figure A1: Population elasticities of skills and years of schooling, all locations



Note: The size of the bubble measures the size of each educational level.
The vertical axis does not start at zero.

Figure A2: Pairwise comparisons of education; all locations versus paper, weighted



Note: The last *bin* does not overlap horizontally since the number of observations is larger for all locatons.

Table A3: Sectoral employment population elasticities, 2000

	Region		Agglomeration		City	
Sector	All	Paper	All	Paper	All	Paper
	(1)	(2)	(3)	(4)	(5)	(6)
Farming	1.041	1.044	1.037	1.013	0.946	0.909
	(0.044)	(0.059)	(0.051)	(0.058)	(0.073)	(0.071)
Construction	1.068	1.007	1.031	1.089	1.012	1.026
	(0.059)	(0.058)	(0.035)	(0.037)	(0.039)	(0.038)
Public Services	0.947	0.863	0.954	1.021	1.044	1.065
	(0.056)	(0.063)	(0.036)	(0.039)	(0.044)	(0.043)
Mining	0.633	0.299	0.703	0.639	0.654	0.665
	(0.106)	(0.113)	(0.097)	(0.108)	(0.121)	(0.123)
Manufacturing	1.276	1.168	1.245	1.260	1.156	1.158
	(0.061)	(0.073)	(0.037)	(0.042)	(0.043)	(0.044)
Trade	0.991	0.962	0.984	1.038	1.024	1.041
	(0.037)	(0.044)	(0.026)	(0.029)	(0.031)	(0.030)
Transport	0.904	0.821	0.895	0.938	0.913	0.935
	(0.046)	(0.049)	(0.025)	(0.024)	(0.032)	(0.030)
Public Utility	0.834	0.847	0.748	0.875	0.820	0.843
	(0.067)	(0.068)	(0.056)	(0.059)	(0.069)	(0.070)
Real Estate	1.122	1.062	1.271	1.249	1.256	1.267
	(0.107)	(0.130)	(0.067)	(0.070)	(0.065)	(0.066)
Utilities	0.783	0.697	0.795	0.806	0.768	0.775
	(0.047)	(0.050)	(0.036)	(0.037)	(0.041)	(0.041)
Research	0.884	0.949	1.016	1.077	1.312	1.354
	(0.073)	(0.103)	(0.067)	(0.072)	(0.075)	(0.072)
Culture	0.915	0.925	0.894	0.941	0.988	1.004
	(0.022)	(0.023)	(0.022)	(0.022)	(0.028)	(0.027)
Public Health	0.888	0.890	0.878	0.917	0.947	0.959
	(0.025)	(0.031)	(0.021)	(0.023)	(0.027)	(0.027)
Public	0.764	0.827	0.792	0.840	0.802	0.816
Administration	(0.020)	(0.026)	(0.025)	(0.025)	(0.032)	(0.031)
Banking	0.869	0.847	0.864	0.894	0.864	0.874
	(0.037)	(0.040)	(0.030)	(0.030)	(0.035)	(0.036)
Observations	5,062	4,439	4,679	4,229	3,929	3,764
R-squared	0.865	0.871	0.852	0.858	0.819	0.824
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: standard errors in parentheses, clustered by relevant spatial unit; all = all locations

Table A4: Sectoral employment population elasticities, 2010

Sector	Region		Agglomeration		City	
	All	Paper	All	Paper	All	Paper
	(1)	(2)	(3)	(4)	(5)	(6)
Farming	0.868	0.823	0.827	0.800	0.662	0.633
	(0.058)	(0.084)	(0.064)	(0.072)	(0.076)	(0.076)
Construction	1.216	1.115	1.042	1.042	1.054	1.066
	(0.052)	(0.036)	(0.028)	(0.028)	(0.028)	(0.028)
Public Services	1.103	1.011	1.090	1.080	1.065	1.073
	(0.041)	(0.040)	(0.025)	(0.026)	(0.025)	(0.025)
Mining	0.634	0.308	0.617	0.543	0.541	0.539
	(0.117)	(0.106)	(0.094)	(0.098)	(0.099)	(0.100)
Hotel	1.008	0.945	1.015	1.004	1.035	1.047
	(0.036)	(0.040)	(0.029)	(0.029)	(0.029)	(0.029)
Manufacturing	1.550	1.433	1.462	1.459	1.368	1.374
	(0.064)	(0.073)	(0.041)	(0.046)	(0.048)	(0.050)
Trade	1.176	1.158	1.137	1.153	1.147	1.156
	(0.029)	(0.035)	(0.021)	(0.021)	(0.023)	(0.023)
Transport	1.041	0.947	0.994	1.013	1.016	1.027
	(0.046)	(0.044)	(0.021)	(0.021)	(0.024)	(0.024)
Public Utility	0.921	0.868	0.960	0.998	1.039	1.056
	(0.059)	(0.056)	(0.036)	(0.038)	(0.037)	(0.037)
Real Estate	1.268	1.213	1.266	1.280	1.362	1.396
	(0.099)	(0.099)	(0.052)	(0.050)	(0.043)	(0.041)
Utilities	0.851	0.725	0.845	0.843	0.852	0.856
	(0.058)	(0.044)	(0.027)	(0.028)	(0.029)	(0.029)
Culture	0.968	0.991	1.029	1.066	1.147	1.170
	(0.050)	(0.062)	(0.041)	(0.044)	(0.041)	(0.039)
Business Services	1.113	1.074	1.094	1.104	1.108	1.118
	(0.032)	(0.036)	(0.021)	(0.021)	(0.021)	(0.021)
Research	1.055	1.113	1.111	1.219	1.380	1.415
	(0.074)	(0.089)	(0.062)	(0.065)	(0.061)	(0.059)
Computer	1.066	1.067	1.079	1.110	1.158	1.172
	(0.044)	(0.056)	(0.036)	(0.040)	(0.038)	(0.039)
Public Health	0.974	0.973	0.946	0.964	0.993	0.995
	(0.025)	(0.027)	(0.018)	(0.019)	(0.021)	(0.021)
Public Administration	0.748	0.826	0.789	0.817	0.837	0.846
	(0.028)	(0.030)	(0.026)	(0.030)	(0.027)	(0.027)
Banking	1.039	1.021	1.028	1.048	1.057	1.066
	(0.042)	(0.050)	(0.028)	(0.031)	(0.031)	(0.032)
Education	0.969	0.972	0.945	0.968	1.007	1.011
	(0.020)	(0.020)	(0.018)	(0.019)	(0.019)	(0.020)
Observations	6,397	5,624	6,003	5,453	5,396	5,149
R-squared	0.871	0.879	0.875	0.880	0.857	0.862
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: standard errors in parentheses, clustered by relevant spatial unit; all = all locations

Table A5: Occupational employment population elasticities, 2000

	Region		Agglomeration		City	
Occupation	All	Paper	All	Paper	All	Paper
	(1)	(2)	(3)	(4)	(5)	(6)
Agriculture	1.041	1.042	1.039	1.013	0.947	0.910
	(0.043)	(0.058)	(0.051)	(0.058)	(0.073)	(0.071)
Production	1.079	0.976	1.073	1.107	1.014	1.026
	(0.056)	(0.061)	(0.032)	(0.036)	(0.037)	(0.037)
Others	0.775	0.713	0.736	0.631	0.643	0.631
	(0.071)	(0.097)	(0.078)	(0.084)	(0.112)	(0.115)
Business Service	0.976	0.938	0.976	1.026	1.016	1.034
	(0.038)	(0.045)	(0.025)	(0.028)	(0.030)	(0.029)
Unit Head	0.871	0.932	0.992	1.047	1.033	1.052
	(0.036)	(0.047)	(0.032)	(0.034)	(0.040)	(0.039)
Clerk	0.888	0.887	0.905	0.944	0.964	0.977
	(0.034)	(0.046)	(0.031)	(0.034)	(0.039)	(0.039)
Technical Personnel	0.879	0.898	0.908	0.955	0.995	1.009
	(0.025)	(0.031)	(0.024)	(0.026)	(0.029)	(0.028)
Observations	2,355	2,062	2,168	1,960	1,815	1,738
R-squared	0.923	0.923	0.915	0.915	0.899	0.899
Occup FE	Yes	Yes	Yes	Yes	Yes	Yes

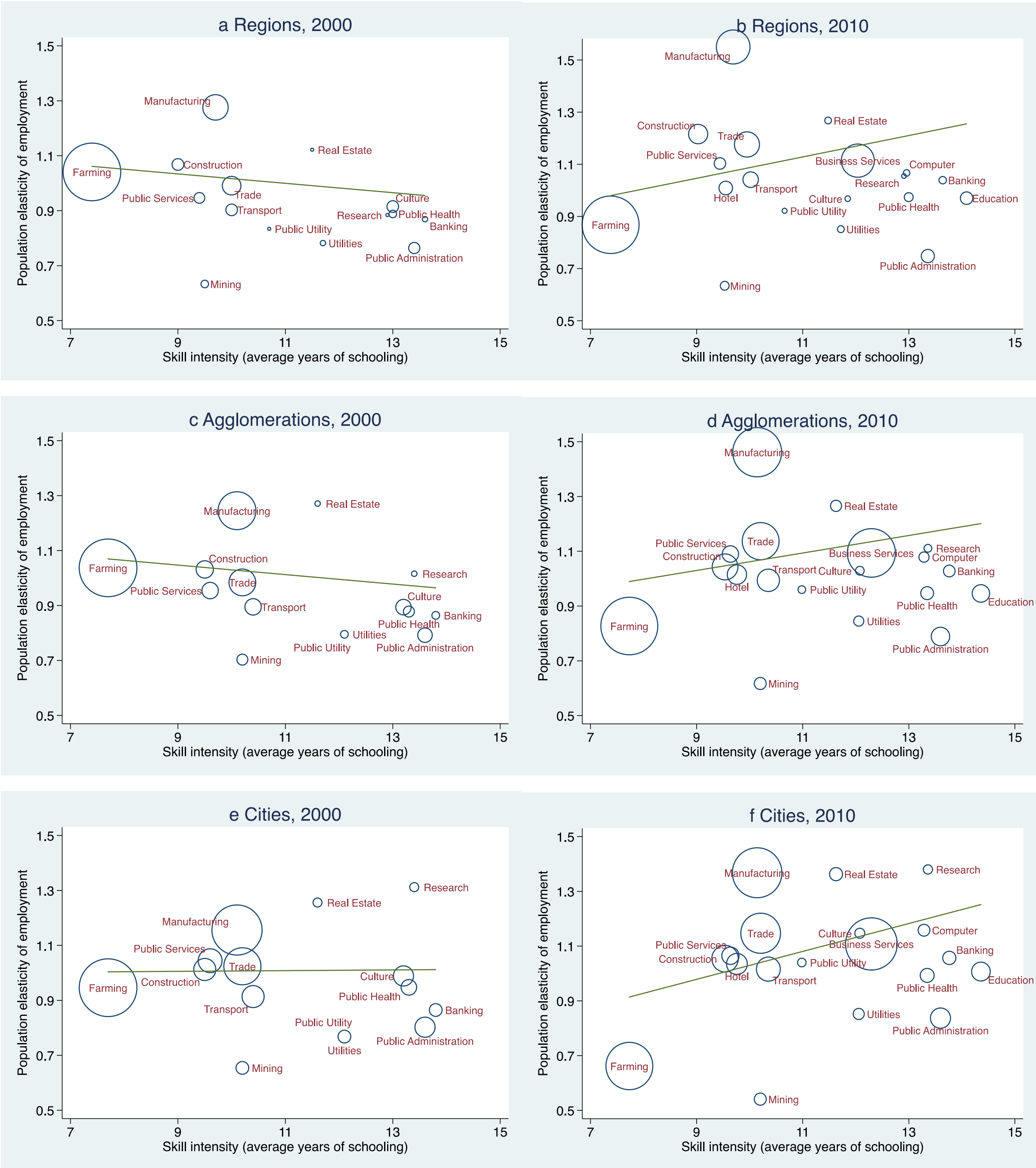
Note: standard errors in parentheses, clustered by relevant spatial unit; all = all locations

Table A6: Occupational employment population elasticities, 2010

	Region		Agglomeration		City	
Occupation	All	Paper	All	Paper	All	Paper
	(1)	(2)	(3)	(4)	(5)	(6)
Agriculture	0.870	0.830	0.817	0.784	0.654	0.624
	(0.058)	(0.084)	(0.061)	(0.068)	(0.073)	(0.073)
Production	1.277	1.164	1.191	1.184	1.136	1.147
	(0.053)	(0.049)	(0.029)	(0.031)	(0.030)	(0.031)
Others	1.143	1.109	1.105	1.139	1.149	1.124
	(0.083)	(0.112)	(0.095)	(0.100)	(0.119)	(0.121)
Business Service	1.113	1.074	1.094	1.104	1.108	1.118
	(0.032)	(0.036)	(0.021)	(0.021)	(0.021)	(0.021)
Unit Head	1.033	1.079	1.165	1.202	1.238	1.255
	(0.041)	(0.056)	(0.035)	(0.038)	(0.035)	(0.036)
Clerk	0.971	1.009	1.003	1.028	1.074	1.090
	(0.036)	(0.046)	(0.031)	(0.035)	(0.032)	(0.032)
Technical Personnel	0.983	1.011	1.018	1.057	1.096	1.106
	(0.029)	(0.036)	(0.024)	(0.026)	(0.024)	(0.024)
Observations	2,352	2,069	2,200	2,000	1,978	1,887
R-squared	0.922	0.922	0.912	0.916	0.899	0.901
Occup FE	Yes	Yes	Yes	Yes	Yes	Yes

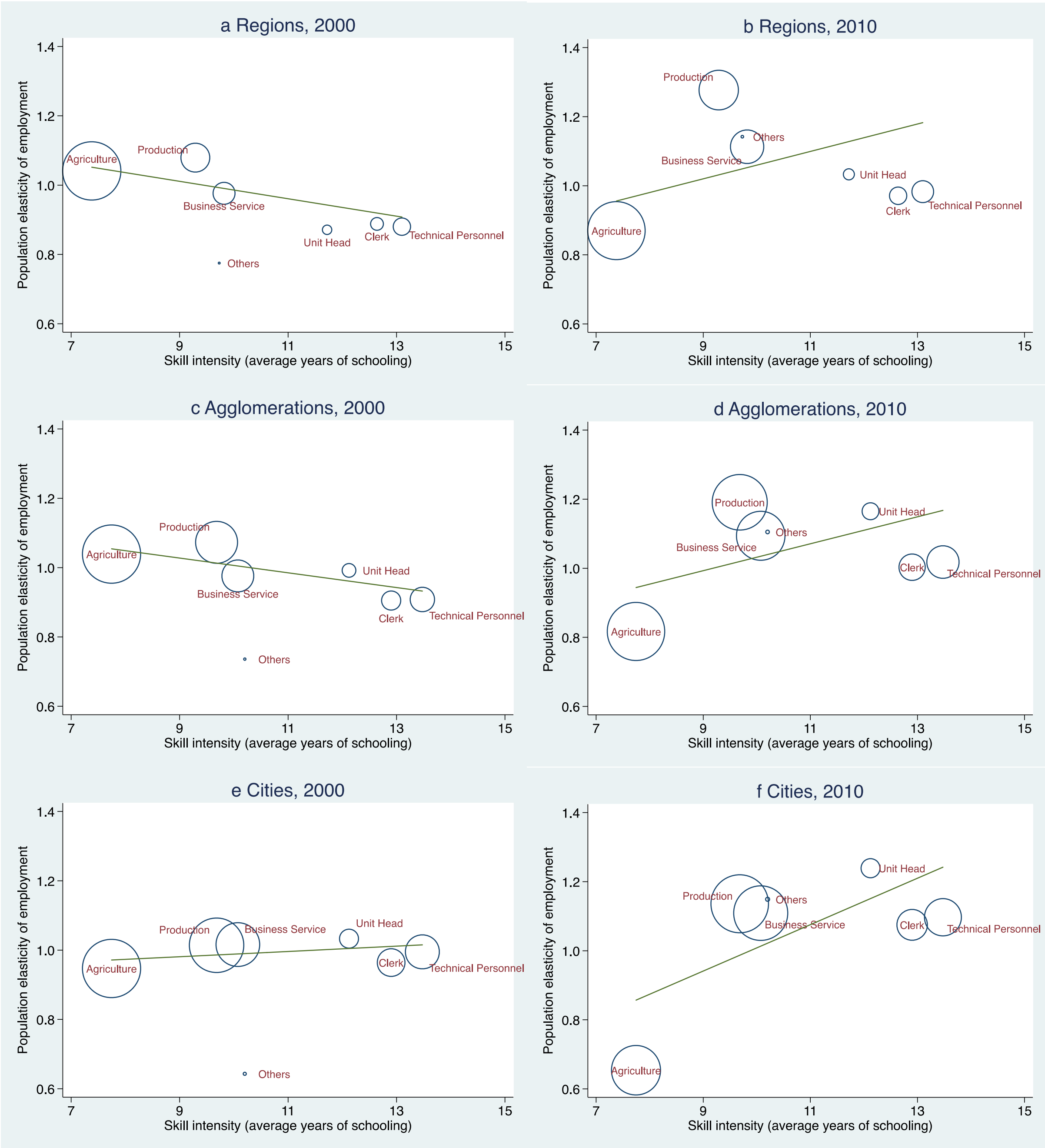
Note: standard errors in parentheses, clustered by relevant spatial unit; all = all locations

Figure A3: Sectors' population elasticities and skill intensities, all locations



Note: The size of the bubble measures the size of sectors.
The vertical axis does not start at zero.

Figure A4: Occupations' population elasticities and skill intensities, all locations



Note: The size of the bubble measures the size of occupations.
The vertical axis does not start at zero.

Table A7: The pairwise comparison for education

2000-Region					2010-Region				
Bin	Pairs	Sample	Unweighted	Weighted	Bin	Pairs	Sample	Unweighted	Weighted
2	15	All	0.867	0.867	2	15	All	1.000	1.000
2	15	Paper	0.933	0.933	2	15	Paper	1.000	1.000
4	90	All	0.667	0.676	4	90	All	0.733	0.761
4	90	Paper	0.633	0.676	4	90	Paper	0.744	0.772
10	675	All	0.584	0.613	10	675	All	0.637	0.679
10	675	Paper	0.604	0.632	10	675	Paper	0.664	0.711
30	6525	All	0.562	0.588	30	6525	All	0.596	0.641
30	6525	Paper	0.579	0.604	30	6525	Paper	0.604	0.653
90	60,075	All	0.535	0.554	90	60,075	All	0.557	0.591
90	60,075	Paper	0.545	0.562	90	60,075	Paper	0.563	0.598
338	854,295	All	0.504	0.506	337	854,295	All	0.515	0.525
296	654,900	Paper	0.507	0.508	296	654,900	Paper	0.526	0.540
2000-Agglomeration					2010-Agglomeration				
Bin	Pairs	Sample	Unweighted	Weighted	Bin	Pairs	Sample	Unweighted	Weighted
2	15	All	0.800	0.800	2	15	All	1.000	1.000
2	15	Paper	1.000	1.000	2	15	Paper	1.000	1.000
4	90	All	0.756	0.770	4	90	All	0.756	0.818
4	90	Paper	0.789	0.804	4	90	Paper	0.856	0.904
10	675	All	0.615	0.649	10	675	All	0.670	0.744
10	675	Paper	0.630	0.660	10	675	Paper	0.693	0.772
30	6525	All	0.586	0.621	30	6525	All	0.615	0.680
30	6525	Paper	0.604	0.645	30	6525	Paper	0.630	0.703
90	60,075	All	0.543	0.576	90	60,075	All	0.587	0.647
90	60,075	Paper	0.550	0.591	90	60,075	Paper	0.594	0.662
312	727,740	All	0.513	0.532	316	746,550	All	0.539	0.576
282	594,315	Paper	0.524	0.550	287	615,615	Paper	0.553	0.598
2000-City					2010-City				
Bin	Pairs	Sample	Unweighted	Weighted	Bin	Pairs	Sample	Unweighted	Weighted
2	15	All	1.000	1.000	2	15	All	1.000	1.000
2	15	Paper	1.000	1.000	2	15	Paper	1.000	1.000
4	90	All	0.722	0.826	4	90	All	0.822	0.908
4	90	Paper	0.733	0.833	4	90	Paper	0.844	0.924
10	675	All	0.610	0.694	10	675	All	0.692	0.818
10	675	Paper	0.579	0.658	10	675	Paper	0.717	0.840
30	6525	All	0.579	0.662	30	6525	All	0.650	0.767
30	6525	Paper	0.566	0.645	30	6525	Paper	0.657	0.772
90	60,075	All	0.550	0.620	90	60,075	All	0.601	0.700
90	60,075	Paper	0.546	0.616	90	60,075	Paper	0.603	0.700
262	512,865	All	0.537	0.592	284	602,790	All	0.565	0.632
251	470,625	Paper	0.536	0.595	271	548,775	Paper	0.567	0.637

Table A8: The pairwise comparison for sectors

2000-Region					2010-Region				
Bin	Pairs	Sample	Unweighted	Weighted	Bin	Pairs	Sample	Unweighted	Weighted
2	105	All	0.429	0.430	2	171	All	0.515	0.552
2	105	Paper	0.448	0.446	2	171	Paper	0.544	0.595
4	630	All	0.435	0.419	4	1026	All	0.480	0.486
4	630	Paper	0.467	0.466	4	1026	Paper	0.512	0.521
10	4725	All	0.441	0.403	10	7695	All	0.467	0.438
10	4725	Paper	0.468	0.456	10	7695	Paper	0.500	0.501
30	45,675	All	0.452	0.407	30	74,385	All	0.476	0.446
30	45,675	Paper	0.479	0.466	30	74,385	Paper	0.496	0.493
90	420,525	All	0.464	0.420	90	684,855	All	0.478	0.448
90	420,525	Paper	0.484	0.469	90	684,855	Paper	0.497	0.497
338	5,980,065	All	0.479	0.442	337	9,681,336	All	0.482	0.456
296	4,584,300	Paper	0.489	0.475	296	7,465,860	Paper	0.493	0.487
2000-Agglomeration					2010-Agglomeration				
Bin	Pairs	Sample	Unweighted	Weighted	Bin	Pairs	Sample	Unweighted	Weighted
2	105	All	0.467	0.462	2	171	All	0.544	0.581
2	105	Paper	0.505	0.551	2	171	Paper	0.579	0.624
4	630	All	0.429	0.410	4	1026	All	0.460	0.480
4	630	Paper	0.470	0.477	4	1026	Paper	0.494	0.515
10	4725	All	0.427	0.395	10	7695	All	0.444	0.444
10	4725	Paper	0.443	0.424	10	7695	Paper	0.452	0.462
30	45,675	All	0.438	0.406	30	74,385	All	0.458	0.452
30	45,675	Paper	0.443	0.416	30	74,385	Paper	0.472	0.473
90	420,525	All	0.449	0.412	90	684,855	All	0.468	0.458
90	420,525	Paper	0.453	0.419	90	684,855	Paper	0.475	0.474
312	5,094,180	All	0.467	0.439	316	8,510,670	All	0.475	0.464
282	4,160,205	Paper	0.470	0.444	287	7,018,011	Paper	0.483	0.481
2000-City					2010-City				
Bin	Pairs	Sample	Unweighted	Weighted	Bin	Pairs	Sample	Unweighted	Weighted
2	105	All	0.457	0.445	2	171	All	0.579	0.623
2	105	Paper	0.467	0.461	2	171	Paper	0.579	0.613
4	630	All	0.437	0.473	4	1026	All	0.487	0.550
4	630	Paper	0.433	0.479	4	1026	Paper	0.485	0.548
10	4725	All	0.436	0.444	10	7695	All	0.459	0.503
10	4725	Paper	0.445	0.458	10	7695	Paper	0.455	0.505
30	45,675	All	0.461	0.459	30	74,385	All	0.479	0.516
30	45,675	Paper	0.459	0.463	30	74,385	Paper	0.476	0.514
90	420,525	All	0.468	0.465	90	684,855	All	0.488	0.518
90	420,525	Paper	0.468	0.468	90	684,855	Paper	0.488	0.520
262	3,590,055	All	0.481	0.479	284	6,871,806	All	0.491	0.511
251	3,294,375	Paper	0.482	0.483	271	6,256,035	Paper	0.492	0.513

Table A9: The pairwise comparison for occupations

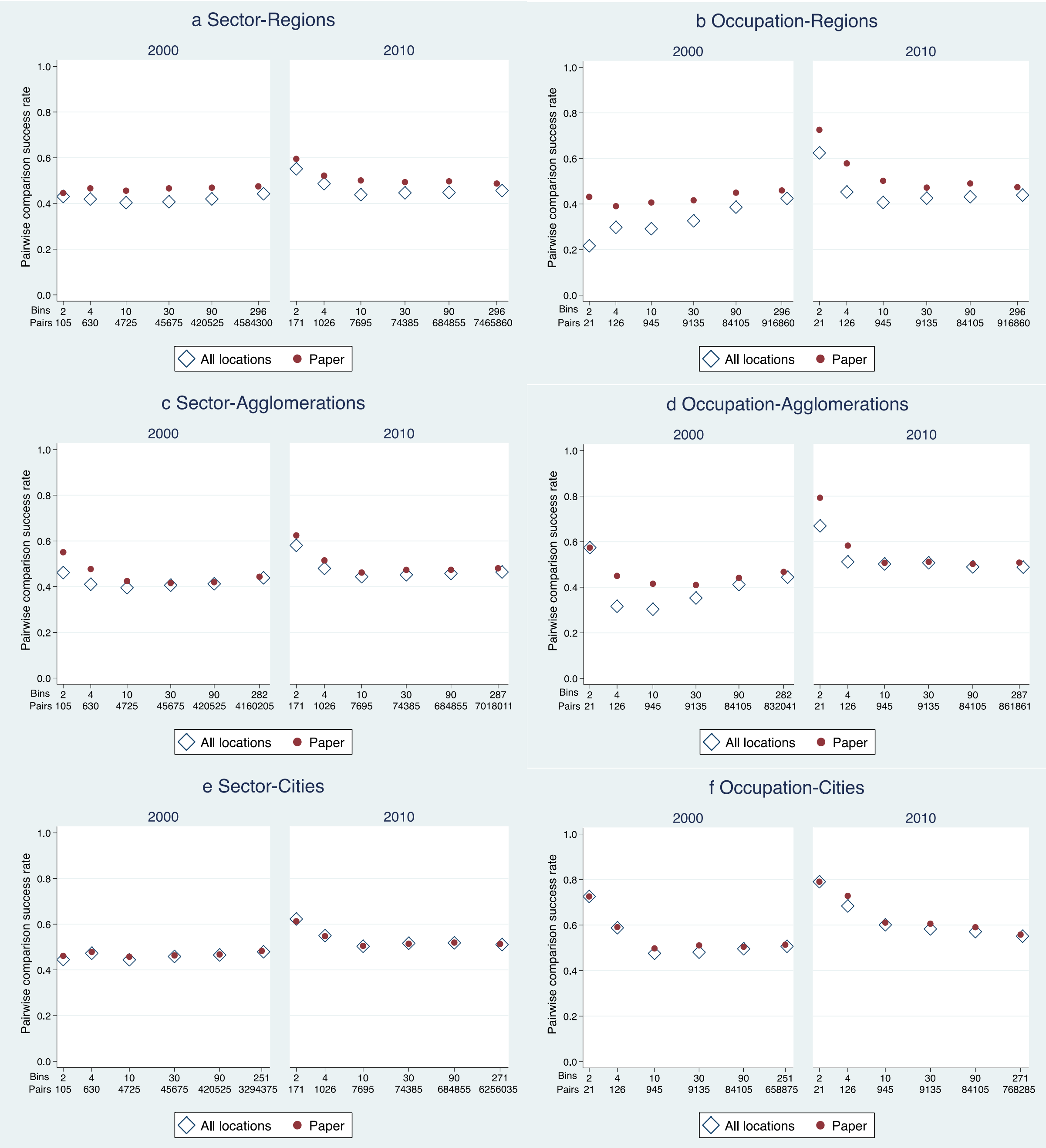
2000-Region					2010-Region				
Bin	Pairs	Sample	Unweighted	Weighted	Bin	Pairs	Sample	Unweighted	Weighted
2	21	All	0.286	0.216	2	21	All	0.524	0.624
2	21	Paper	0.381	0.432	2	21	Paper	0.619	0.726
4	126	All	0.357	0.298	4	126	All	0.421	0.453
4	126	Paper	0.405	0.391	4	126	Paper	0.524	0.578
10	945	All	0.363	0.291	10	945	All	0.410	0.407
10	945	Paper	0.426	0.407	10	945	Paper	0.469	0.502
30	9135	All	0.411	0.326	30	9135	All	0.446	0.426
30	9135	Paper	0.449	0.416	30	9135	Paper	0.466	0.472
90	84,105	All	0.447	0.386	90	84,105	All	0.456	0.432
90	84,105	Paper	0.474	0.450	90	84,105	Paper	0.485	0.490
338	1,196,013	All	0.467	0.425	337	1,188,936	All	0.463	0.439
296	916,860	Paper	0.483	0.460	296	916,860	Paper	0.480	0.474
2000-Agglomeration					**2010-Agglomeration**				
Bin	Pairs	Sample	Unweighted	Weighted	Bin	Pairs	Sample	Unweighted	Weighted
2	21	All	0.429	0.574	2	21	All	0.524	0.669
2	21	Paper	0.429	0.574	2	21	Paper	0.667	0.793
4	126	All	0.278	0.316	4	126	All	0.381	0.511
4	126	Paper	0.357	0.450	4	126	Paper	0.460	0.583
10	945	All	0.338	0.303	10	945	All	0.419	0.502
10	945	Paper	0.402	0.415	10	945	Paper	0.430	0.507
30	9135	All	0.395	0.353	30	9135	All	0.456	0.507
30	9135	Paper	0.416	0.410	30	9135	Paper	0.460	0.511
90	84,105	All	0.434	0.412	90	84,105	All	0.465	0.489
90	84,105	Paper	0.448	0.441	90	84,105	Paper	0.474	0.502
312	1,018,836	All	0.462	0.444	316	1,045,170	All	0.480	0.488
282	832,041	Paper	0.471	0.467	287	861,861	Paper	0.490	0.508
2000-City					**2010-City**				
Bin	Pairs	Sample	Unweighted	Weighted	Bin	Pairs	Sample	Unweighted	Weighted
2	21	All	0.571	0.726	2	21	All	0.619	0.791
2	21	Paper	0.571	0.726	2	21	Paper	0.619	0.791
4	126	All	0.484	0.588	4	126	All	0.484	0.684
4	126	Paper	0.476	0.591	4	126	Paper	0.532	0.728
10	945	All	0.443	0.476	10	945	All	0.453	0.601
10	945	Paper	0.449	0.498	10	945	Paper	0.458	0.611
30	9135	All	0.460	0.481	30	9135	All	0.478	0.583
30	9135	Paper	0.471	0.511	30	9135	Paper	0.486	0.606
90	84,105	All	0.475	0.496	90	84,105	All	0.499	0.571
90	84,105	Paper	0.476	0.505	90	84,105	Paper	0.502	0.591
262	718,011	All	0.491	0.507	284	843,906	All	0.504	0.551
251	658,875	Paper	0.492	0.514	271	768,285	Paper	0.505	0.558

Table A10: Comparison of regression slopes; all locations versus paper

			Slope Paper	Slope All	Significant difference?	Std. Err.	t	P>|t|	95% Conf. interval	
Education	Region	2000	0.012	0.028	No	0.017	0.90	0.397	-0.024	0.055
		2010	0.017	0.022	No	0.012	0.42	0.687	-0.023	0.034
	Agglomeration	2000	0.012	0.010	No	0.009	-0.24	0.813	-0.023	0.019
		2010	0.020	0.016	No	0.008	-0.48	0.644	-0.021	0.014
	City	2000	0.015	0.015	No	0.011	-0.08	0.942	-0.025	0.024
		2010	0.027	0.026	No	0.011	-0.13	0.903	-0.026	0.023
Sector	Region	2000	-0.025	-0.017	No	0.022	0.36	0.719	-0.038	0.054
		2010	0.046	0.041	No	0.038	-0.13	0.901	-0.083	0.073
	Agglomeration	2000	-0.002	-0.017	No	0.026	-0.57	0.576	-0.069	0.040
		2010	0.041	0.032	No	0.049	-0.19	0.852	-0.108	0.090
	City	2000	0.012	0.001	No	0.027	-0.40	0.696	-0.067	0.046
		2010	0.057	0.051	No	0.063	-0.10	0.921	-0.135	0.122
Occupation	Region	2000	-0.029	-0.025	No	0.007	0.53	0.604	-0.012	0.019
		2010	0.049	0.040	No	0.044	-0.21	0.835	-0.107	0.088
	Agglomeration	2000	-0.006	-0.021	No	0.011	-1.35	0.206	-0.041	0.010
		2010	0.052	0.039	No	0.051	-0.26	0.802	-0.126	0.100
	City	2000	0.017	0.008	No	0.013	-0.76	0.467	-0.037	0.018
		2010	0.074	0.067	No	0.065	-0.11	0.918	-0.151	0.137

Note: the table reports the slopes of the regression lines in Figures 3, 5, and 6 of the paper and compares with the slopes of the regression lines in Figures A1, A3, and A4 of the Appendix; a two-sided test is used at the 5% level; the null hypothesis is that the slopes are identical; all = all locations.

Figure A5: Pairwise comparisons of sectors and occupations; all locations versus paper, weighted



Note: The last *bin* does not overlap horizontally since the number of observations is larger for all locatons.

Figure A6 Population elasticities and pairwise comparison of six educational attainments in 2010 with location type as specified in 2000

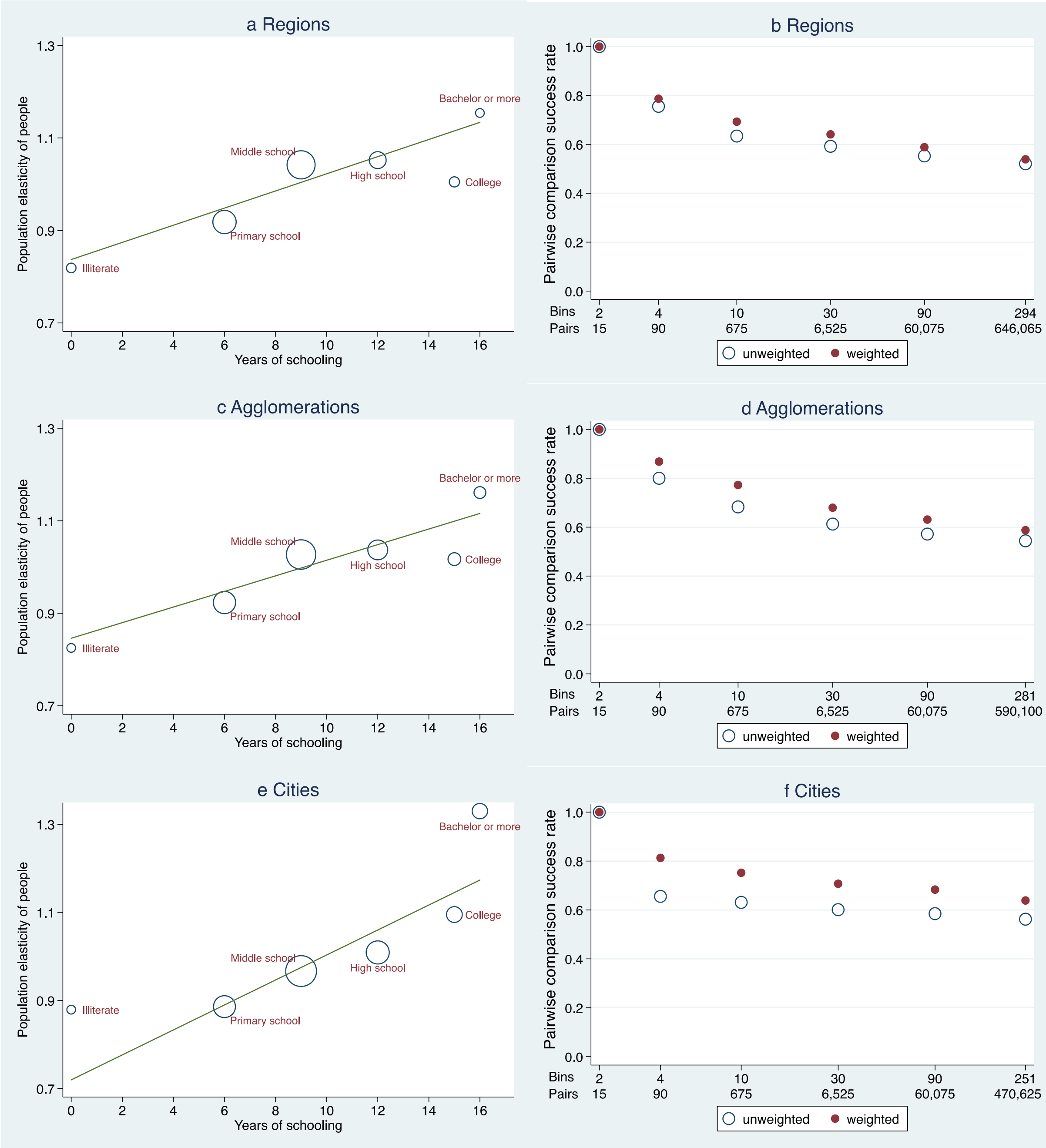


Figure A7 Sectors' and occupations' population elasticities relative to skill intensities in 2010 with location type as specified in 2000

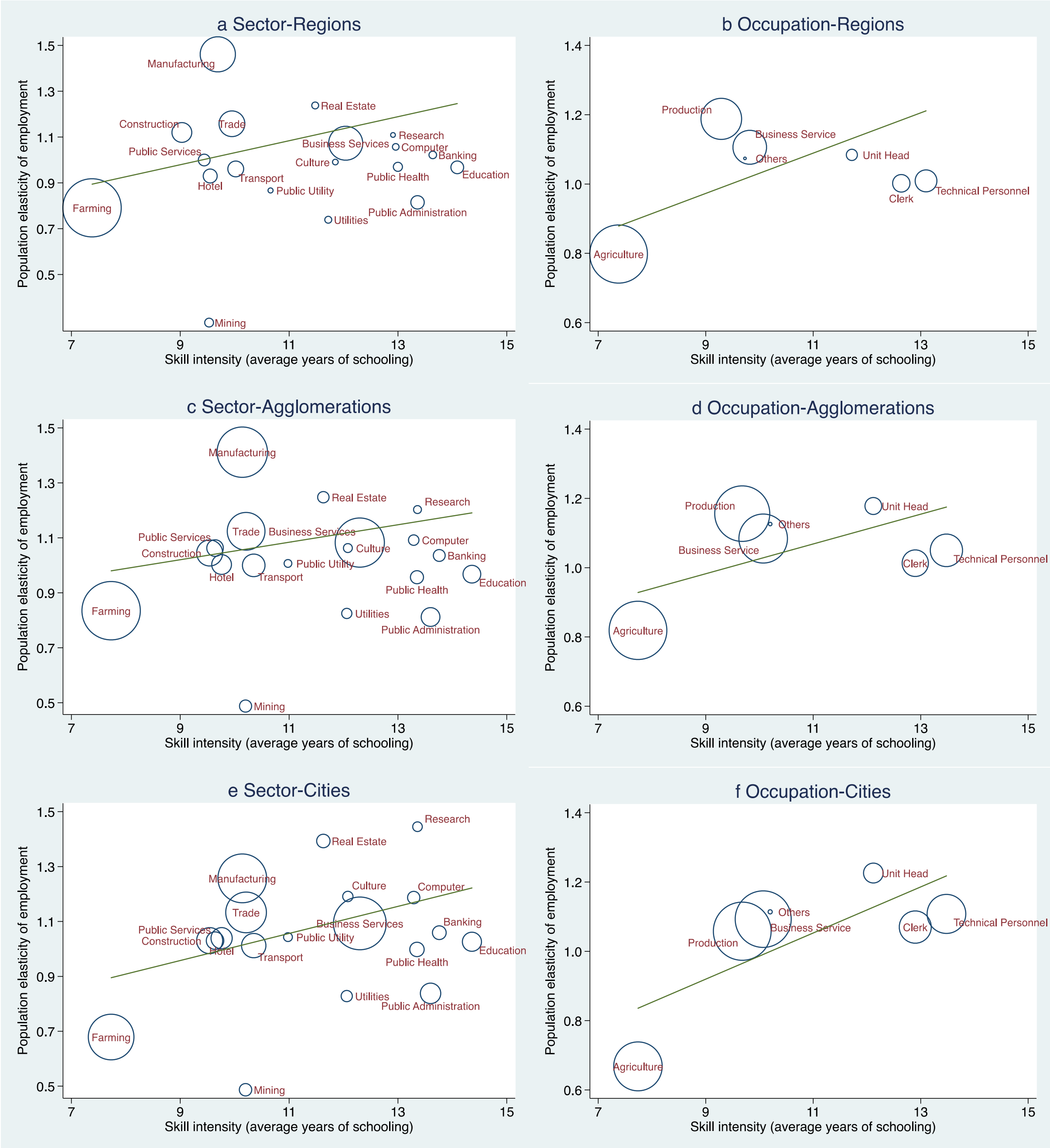
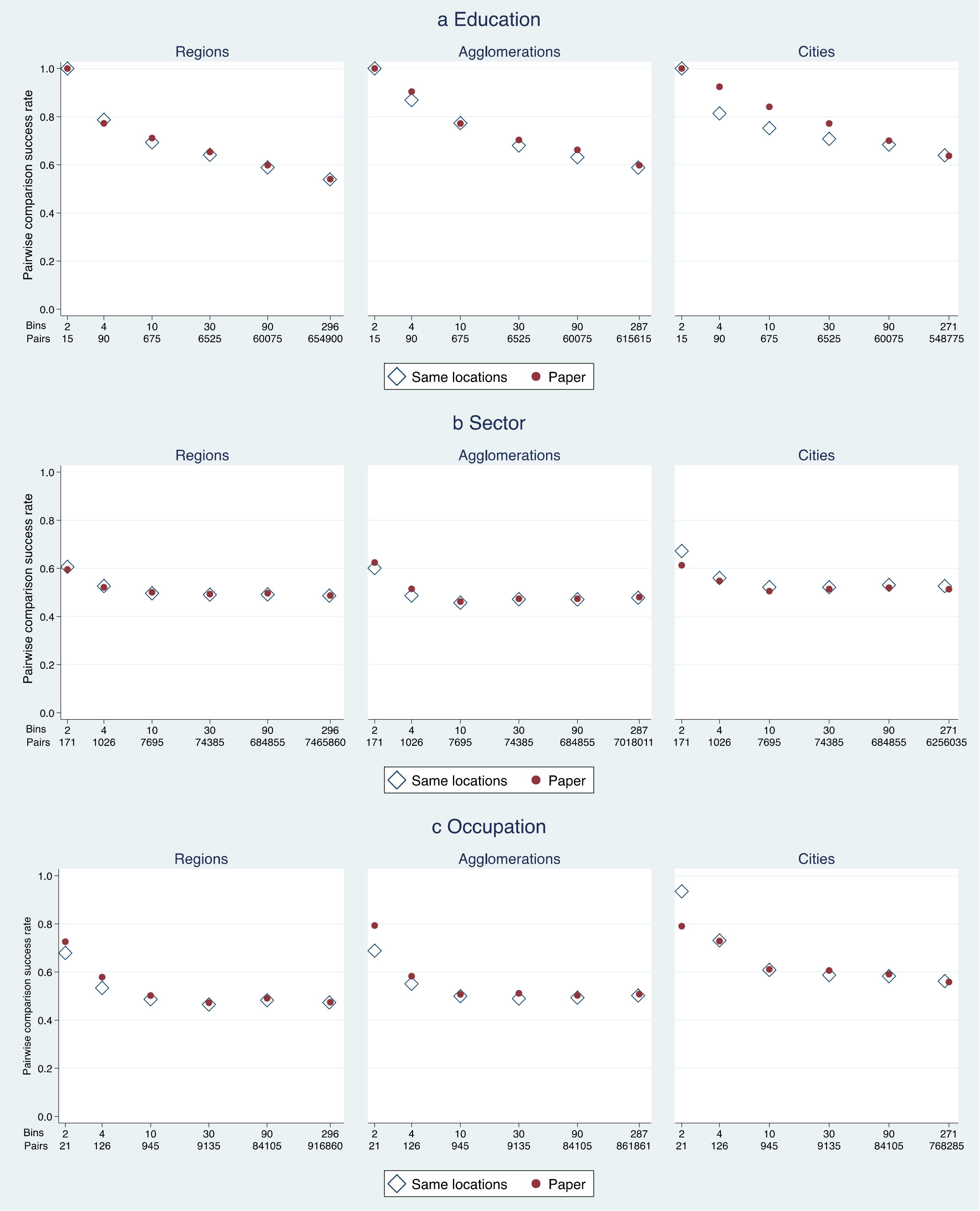


Figure A8: Pairwise comparisons in 2010 with location type as specified in 2000; same location versus paper, weighted



Note: The last *bin* does not overlap horizontally since the number of observations is smaller for same locations.

Table A11: Comparison of regression slopes in 2010; same location versus paper

		Slope Paper	Slope Same type	Significant difference?	Std. Err.	t	P>|t|	95% Conf. interval	
Education	Region	0.017	0.019	No	0.007	0.21	0.838	-0.014	0.017
	Agglomeration	0.020	0.017	No	0.007	-0.42	0.688	-0.018	0.013
	City	0.027	0.028	No	0.012	0.08	0.938	-0.028	0.030
Sector	Region	0.046	0.052	No	0.037	0.18	0.858	-0.068	0.081
	Agglomeration	0.041	0.032	No	0.046	-0.20	0.843	-0.103	0.085
	City	0.057	0.049	No	0.059	-0.14	0.892	-0.127	0.111
Occupation	Region	0.049	0.058	No	0.043	0.22	0.833	-0.086	0.104
	Agglomeration	0.052	0.043	No	0.047	-0.19	0.852	-0.114	0.096
	City	0.074	0.067	No	0.059	-0.13	0.902	-0.138	0.123

Note: the table reports the slopes of the regression lines for 2010 in Figures 3, 5, and 6 of the paper and compares with the slopes of the regression lines in Figures A6 and A7 of the Appendix; a two-sided test is used at the 5% level; the null hypothesis is that the slopes are identical; same type = corrected for location type changes.

Figure A9 Population elasticities and pairwise comparison of sectors in 2010 with sector definition as in 2000

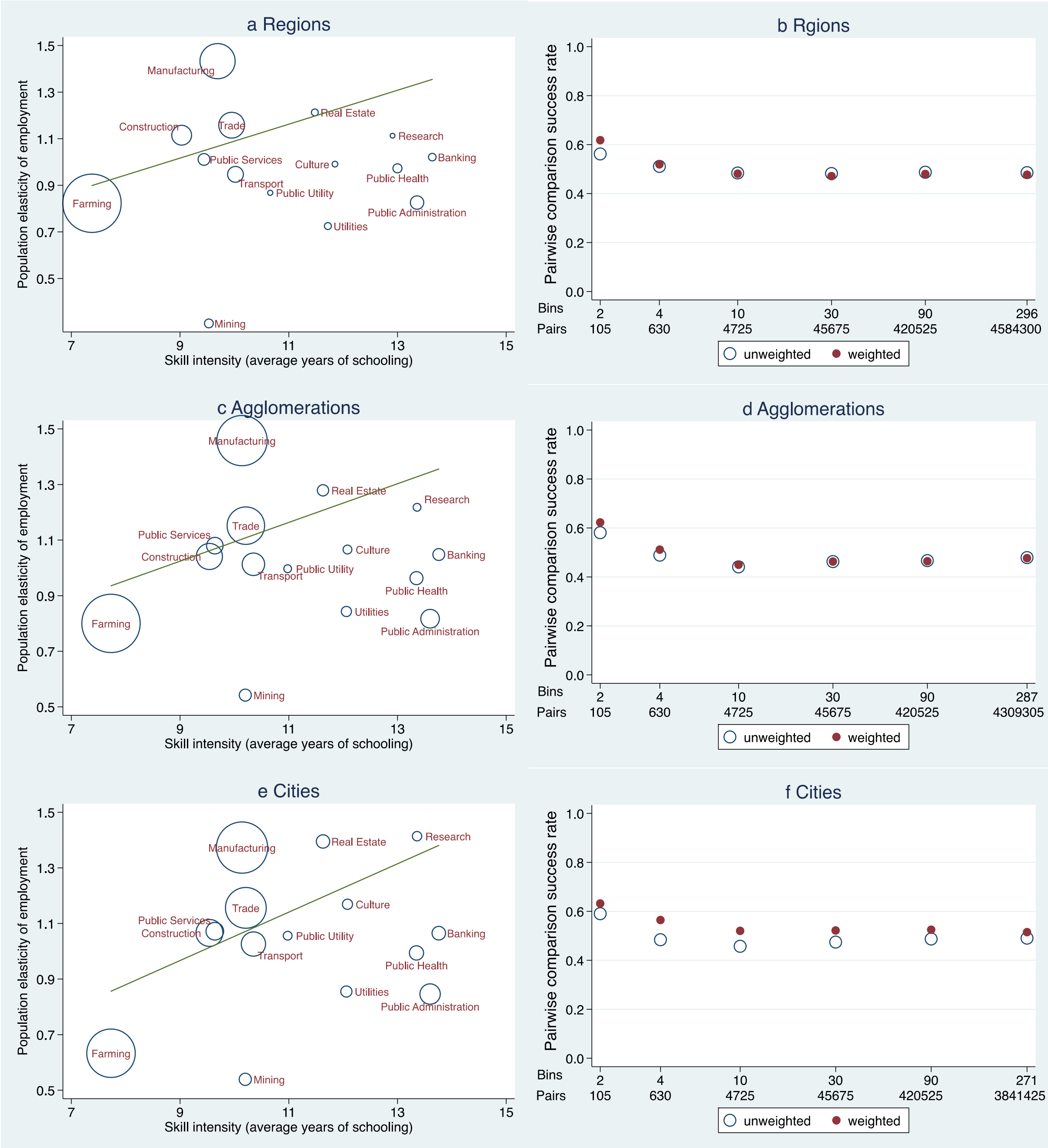


Table A12: Comparison of regression slopes in 2010, same sectors as in 2000

		Slope Paper	Slope Same sector	Significant difference?	Std. Err.	t	P>|t|	95% Conf. interval	
	Region	0.046	0.073	No	0.051	0.53	0.602	-0.077	0.132
Sector	Agglomeration	0.041	0.070	No	0.062	0.46	0.648	-0.098	0.156
	City	0.057	0.087	No	0.077	0.39	0.702	-0.127	0.187

Note: the table reports the slopes of the regression lines for 2010 in Figure 5 of the paper and compares with the slopes of the regression lines in Figure A9 of the Appendix; a two-sided test is used at the 5% level; the null hypothesis is that the slopes are identical; same sector = same sectors as in 2000.