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MANUFACTURING (CO)AGGLOMERATION IN A TRANSITION COUNTRY: EVIDENCE FROM RUSSIA

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Manufacturing (co)agglomeration in a transition country: Evidence from Russia*

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Abstract

We document geographic concentration patterns of Russian manufacturing using microgeographic data. About 42–52% of 4-digit and 63–75% of 3-digit industries are localized, with a higher share in the European part than in the Asian part. About 70% of 3-digit industry pairs are coagglomerated, especially those with stronger buyer-supplier links, more knowledge sharing, and lower transport costs. Pairs with a more similar workforce are, however, less coagglomerated, which points to impediments in labor mobility between regions and firms. Overall, the agglomeration forces are fairly similar to those operating in developed countries, with transportation likely to be a key driver.

Keywords: agglomeration; coagglomeration; determinants of geographic concentration; manufacturing industries; Russia.

JEL classification: R12

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1 Introduction

The uneven spatial distribution of industries is a first-order feature of almost any country in the world. While this has been extensively documented for developed countries—especially for manufacturing—there is a dearth of evidence for developing or transition countries (see World Bank, 2009; Duranton, 2015). This is unfortunate because it is precisely for those countries that understanding geographic concentration—especially for manufacturing—and the associated productivity gains is important to assess economic development prospects and options.

There is now a broad consensus that agglomeration has a causal effect on productivity due to the existence of agglomeration economies: doubling the size of an industry in a geographic area increases productivity by about 2–5% on average (Rosenthal and Strange, 2004; Melo, Graham, and Noland, 2009; Combes and Gobillon, 2015). Realizing these productivity gains from geographic concentration may be especially important for transition countries such as Russia. It has repeatedly been pointed out that Russia needs to reduce its dependence on oil and primary goods, and that it must substantially improve its weak manufacturing productivity. According to Deloitte's *2016 Global Manufacturing Competitiveness Index*, Russia ranks 32 out of 40 countries—lower than Brazil, South Africa, and Poland. It has lost 4 ranks since 2013 and is projected to stay at its current rank in 2020.[1] There is clearly room for substantial improvements, and those may be partly achieved by policies that require a better understanding of geographic concentration patterns and their underlying determinants.

The aim of our paper is twofold. First, we provide a detailed picture of the geographic concentration patterns of Russian manufacturing industries. Using recent and highly disaggregated point-pattern data, we estimate the agglomeration of industries and the coagglomeration of industry pairs.[2] We pay specific attention to Russia's 'dual geographic structure', i.e., the existence of a dense western and a scattered eastern part. Second, we investigate the determi-

[1]Available online at `https://www2.deloitte.com/global/en/pages/manufacturing/articles/global-manufacturing-competitiveness-index.html`, last accessed on February 15, 2018. According to the *Global Competitiveness Report 2014–2015*, Russia ranks 119 out of 144 countries in terms of its goods market competition and efficiency. See `http://www3.weforum.org/docs/WEF_GlobalCompetitivenessReport_2014-15.pdf`, last accessed on February 20, 2018.

[2]There are only few works on geographic concentration in Russia. They all use either the Herfindal-Hirschman Index, or the Krugman Dissimilarity Index, or the Theil Index; and all rely on fairly aggregated regional and industrial data. See, e.g., Kolomak (2015); Rastvortseva and Chentsova (2015); and Maslikhina (2017). We are aware of two papers that use more disaggregated data. Vorobyev, Kislyak, and Davidson (2010) use a sample of about 10,000 firms coded to the city level to estimate localization and urbanization economies for different broad industries. Kofanov, Mihailova, and Shurygin (2015) use a sample of plants—taken from the industrial census of the USSR in 1989 and coded to the settlement level—to look for differences in the geographic structure of manufacturing industries between the Soviet state-planned economy and the free market economy starting in the early 1990s. Neither paper provides estimates for coagglomeration patterns of industry pairs or an analysis of the determinants of agglomeration.

nants of the geographic concentration of individual industries and of the coagglomeration of industry pairs. Little is known to our knowledge about the former, whereas the latter has not been investigated at all for Russia until now. Using high-quality Canadian and U.S. industry-level data to proxy missing Russian data, we investigate how buyer-supplier links, similarity in labor requirements, knowledge sharing, and transportation costs drive the agglomeration and coagglomeration of industries. Understanding the role played by these economic variables is key in devising policies that aim to harness the potential productivity gains from the geographic concentration of industries.

Our key results may be summarized as follows. First, we document strong spatial patterns. About 42–52% of 4-digit industries and 63–75% of 3-digit industries are significantly agglomerated, with a substantially higher share in the European part than in the Asian part of Russia. Roughly 70% of industry pairs are significantly coagglomerated, mainly at short distances below 100 kilometers. Second, the overall patterns of geographic concentration—both their extent, strength, and composition—are surprisingly similar to those documented for manufacturing industries in other countries such as the UK, Canada, or the U.S. Hence, geographic concentration seems to obey similar rules, despite Russia's long history of a centrally-planned economy that explains in large part the geographic structure of industry before 1990 (e.g., Kofanov et al., 2015). Third, we find that the mechanisms associated with geographic concentration in Russia are also similar to those operating in other countries. Stronger buyer-supplier links yield more geographically concentrated patterns, and the same holds true for industry pairs that exchange more knowledge as measured by patent citations data. The only substantive difference that we find compared to other countries is that industries with a more similar workforce tend to be less coagglomerated. This may be explained by specific aspects of the Russian labor market, where low-skilled workers in manufacturing—the bulk of the workforce in that sector—are not mobile between regions and firms. Furthermore, firm-specific non-portable training of the workforce further reduces the mobility of workers between firms.

One of our most interesting findings is the key role played by transport costs. We consistently find that industries that face higher transport costs—measured using industry-level ad valorem trucking costs—are more geographically dispersed than industries that face lower transport costs. This finding, which is in line with the new economic geography (Krugman, 1991) and with recent evidence for Canada (see Behrens, Bougna, and Brown, 2018; and Behrens and Brown, 2018), suggests that geographic concentration is stronger when transport costs are low. It hints at one policy lever that may be used to potentially influence the spatial structure of economic activity and to obtain more agglomeration. This finding may be important for Russia. Although there is substantial infrastructure in the western part of the country, the transport system is partially overloaded, is being worn out rapidly through excessive use, and degrades quickly do to its inferior quality.[3] In the rest of the country, especially

[3]According to the *Global Competitiveness Report 2014–2015*, Russia ranks 124 out of 144 countries in terms of

the east and the far east, infrastructure is either non-existent or close to being non-existent. Our results suggest that cheap transportation—via better infrastructure and more deregulated transport markets—may be required to increase geographic concentration. Yet, one needs to keep in mind that this may give rise to persistent patterns of regional divergence, where most economic activity is concentrated in a few core regions at the expense of relatively deserted peripheries. Such a development would conflict with most regional development objectives for Russian regions that rank traditionally high on the policy agenda.[4]

The remainder of the paper is structured as follows. Section 2 briefly presents our data. Section 3 explains our estimation strategy and summarizes our results for the agglomeration of individual manufacturing industries and the coagglomeration of industry pairs. We provide results for all of Russia, as well as for the western and the eastern parts separately. Section 4 contains our analysis of the determinants of agglomeration and coagglomeration in Russia. Finally, Section 5 concludes and discusses the policy implications of our main findings. Detailed explanations of our data and additional results are relegated to a set of appendices.

2 Data

We start with a brief overview of our data. Additional technical details concerning the data collection and processing, as well as the different data sources, are relegated to Appendix A.1. Our main dataset is the 2014 RUSLANA database, which contains information about Russian companies and establishments.[5] We focus on the manufacturing portion of the database and retain all establishments that were active in 2014 and whose contact information—especially address—were updated between 2012 and 2014. After basic data cleaning and geocoding, using a three-stage procedure detailed in Appendix A.2, we obtain a database with 345,384 geocoded establishments. Of these, we use the 320,934 establishments that are geocoded precisely.

Each establishment reports a primary industry code from the National Industry Classification (OKVED 2007), which is similar to the NACE Rev.2 classification at the 4-digit level. We

quality of its roads. See http://www3.weforum.org/docs/WEF_GlobalCompetitivenessReport_2014-15.pdf, last accessed on February 20, 2018. Regardless of the fact that roads are in poor condition and that even the federal motorways have only two lanes (one in each direction), the most efficient way to transport cargo in Russia is by road. The main reasons are because the labor used in transportation is so cheap, and because the remaining infrastructure is under the control of monopolies such as Aeroflot or the Russian Railway Company.

[4]The uneven development of the Russian regions is highly discussed, especially when it comes to the distribution of budgets. According to Kolomak (2013), labor and capital have flowed towards more productive and amenity-rich regions during 1990–2005, while state capital investment shifted in the opposite direction, maybe to partly counter this trend. The Russian government announced different approaches to regional policy over the last years, but none of these seem to have succeeded. The question concerning the well-balanced development of regions is still relevant in Russia (see, e.g., Ivanova, 2018, for a recent application to Russian cities).

[5]In what follows, we use interchangeably the terms 'establishments' and 'plants'. They both refer to the physical location where firms operate some part of their activities.

use industry codes up to the 4-digit level. Although finer levels are reported by a number of establishments, doing so was not legally mandatory prior to 2012. Hence, samples with industry codes beyond the 4-digit level may be of unreliable coverage. The manufacturing sector is delimited by OKVED 15.00.00 to 37.20.70.[6] We thus end up with a final dataset of 319,684 establishments out of the 320,934 that are precisely geocoded and which report industry information. Table 14 in Appendix A provides a breakdown of establishments by 3-digit industry codes.

Figure 1: Distribution of manufacturing plants in Russia, with east-west divide.

The establishments in our database are geocoded using address information from 2012, 2013, and 2014. We consider that the 2014 address information is the most precise, whereas the 2012 and 2013 information may be less up-to-date. Limiting ourselves to companies with address information in 2014, we have a total number of 178,138 establishments. We refer to this sample as the '*small sample*'. Adding the establishments with 2013 address information yields the *medium sample* (256,943 establishments); while adding the establishments with 2012 address information yields the *large sample* (319,684 establishments). The large and medium samples could be a bit noisier since they may contain establishments that are no longer located at the reported address; yet, these samples are also likely to be more representative of the overall distribution of activity.

[6]For a small number of establishments, we only have industry information at the 2-digit level. We keep those establishments and group them into their 2-digit industry. These results should be read with caution.

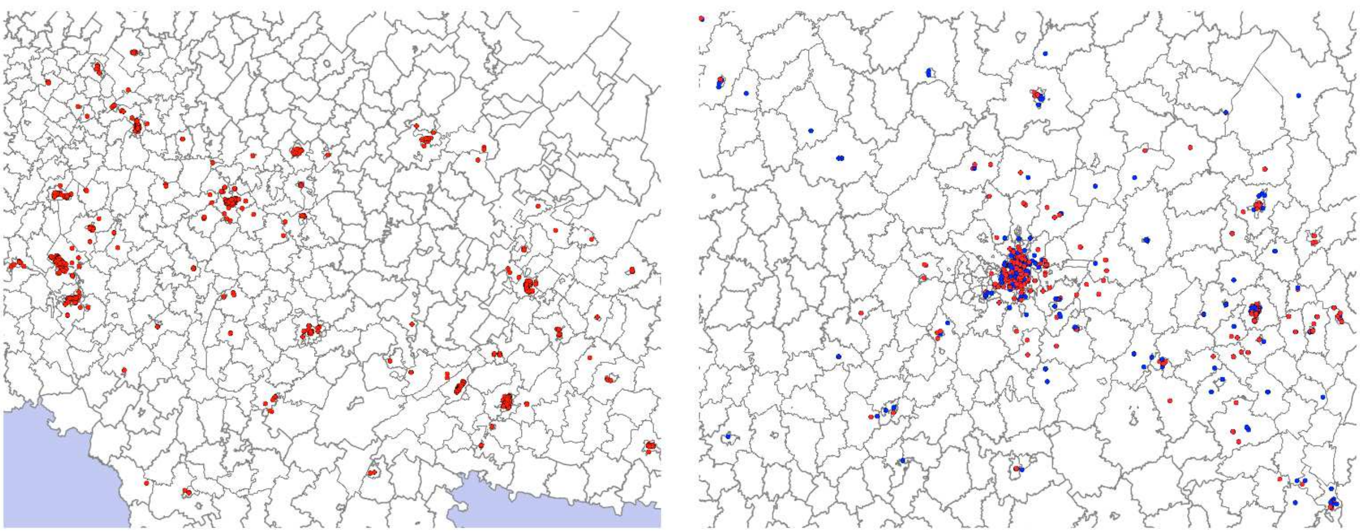
Russia is a geographically large country with a quite dense European part (the west) and a more scattered Asian part (the east). These two parts display very different settlement and population patterns. They are also naturally separated by the north-south range of the Ural mountains (see Appendix A for additional details). To account for this heterogeneity, we will consider the overall spatial distribution of industries in Russia, but also the distributions in the east and in the west separately. Figure 1 depicts the spatial distribution of all manufacturing establishments—using the large sample—in Russia in 2014, and shows the east-west division along the Ural mountains. As can be seen, manufacturing establishments are densely packed in the western part, whereas the eastern part displays a much sparser and more scattered pattern that essentially follows the Trans-Siberian railway line.

3 Geographic agglomeration and coagglomeration patterns

Our aim is to measure the geographic concentration of manufacturing industries in Russia. Figure 2 illustrates two types of patters: the agglomeration of a single industry ('Manufacture of motor vehicles, trailers and semi-trailers', OKVED 34) in panel (a); and the coagglomeration of two industries ('Spinning of textile fibres', OKVED 171; and 'Weaving manufacture', OKVED 172) in panel (b). We will successively look at these two types of geographic concentration.

Figure 2: Examples of 2-digit agglomeration and 3-digit coagglomeration patterns.

(a) Motor vehicles trailers, semi-trailers. (b) Spinning (blue) and weaving (red).



3.1 Agglomeration: Methodology

We follow Duranton and Overman (2005, 2008) who develop a methodology that uses bilateral distances between plants to assess geographic concentration. The idea is to estimate a kernel-smoothed distribution (K-densities) of the bilateral distances between plants, which can then be used to: (i) identify localized industries, i.e., industries that display significantly more geographic concentration than manufacturing in general; and (ii) construct measures of absolute geographic concentration of those industries (see Behrens et al., 2018; and Behrens and Brown, 2018). The idea underlying (i) is to apply sampling and bootstrapping techniques to compare the observed distribution of bilateral distances between the plants in an industry to a set of bilateral distances obtained from samples of randomly drawn plants. Doing so allows to measure *relative geographic concentration*, i.e., how much more—or less—industries are concentrated with respect to manufacturing in general. The idea in (ii) is to construct the cumulative distribution of the K-density up to some distance d, which measures the *absolute geographic concentration* of an industry, namely the share of bilateral distances between plants in that industry below the distance threshold d. These two measures are complementary and capture two different, yet equally important, aspects of the geographic concentration process (see, e.g., Marcon and Puech, 2017, for a recent survey of those measures).

The methodology developed by Duranton and Overman (2005, 2008) involves four steps. First, we compute the pairwise distances between all plants in an industry and estimate a kernel density of their distribution. Second, we construct a counterfactual distribution by assuming that the plants in a given industry are located randomly among all possible locations where we observe manufacturing activity. We use that distribution to estimate a counterfactual kernel density. Third, to assess whether the observed location patterns depart statistically significantly from randomness, we repeat the second step 1,000 times to construct confidence intervals from the 1,000 counterfactual K-densities. Last, we test whether an industry is localized or dispersed or random, by comparing the actual distribution of bilateral distances with the confidence bands derived from the sampling procedure. We now provide more information on these four steps.

First step (kernel densities). Consider an industry A with n plants. We compute the great circle distance d_{ij}, using latitude and longitude coordinates, between each pair (i, j) of establishments in that industry as follows:

$$d_{ij} = 6378.39 \cdot \text{acos}\left[\cos(|\text{lon}_i - \text{lon}_j|)\cos(\text{lat}_i)\cos(\text{lat}_j) + \sin(\text{lat}_i)\sin(\text{lat}_j)\right].$$

Since $d_{ij} = d_{ji}$, this yields $n(n-1)/2$ distinct bilateral distances. The kernel-smoothed estimator of the density of these pairwise distances, henceforth called K-density, at distance d is:

$$\widehat{K}(d) = \frac{2}{n(n-1)h} \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} f\left(\frac{d - d_{ij}}{h}\right), \tag{1}$$

where h is the optimal bandwidth—set according to Silverman's rule of thumb—and $f(\cdot)$ is a Gaussian kernel function. We estimate expression (1) for all $d \leq x$, where x is a cutoff distance that we need to specify in the application. The K-density (1) thus describes the distribution of bilateral distances between establishments in a given industry. Since the K-density is a distribution function, we can also compute its cumulative (CDF) up to some distance $\overline{d} \leq x$:

$$\mathrm{CDF}(\overline{d}) = \sum_{d=0}^{\overline{d}} \widehat{K}(d). \tag{2}$$

The CDF at distance $\overline{d}$ thus measures the share of establishment pairs that are located less than distance $\overline{d}$ from each other. Alternatively, we can view this as the probability that two randomly drawn establishments in an industry will be at most $\overline{d}$ kilometers away from one another. Larger values of the CDF for a given distance indicate industries that have more compact geographic location patterns.

Second step (counterfactual densities). Using the locations of all manufacturing establishements in our sample, we randomly draw as many locations as there are plants in industry A. To each of these locations, we randomly assign a plant from industry A. We then compute the bilateral distances of this hypothetical distribution and estimate the associated counterfactual K-density (1) of these bilateral distances. This procedure ensures that we control for the overall pattern of geographic concentration in the manufacturing sector, as well as for the differences in industry sizes.

Third step (confidence bands). For each industry A, we repeat the second step 1,000 times. This yields a set of 1,000 estimated values of the K-density at each distance d. We then use our bootstrap distribution of K-densities, generated by the counterfactuals, to construct a two-sided confidence band that contains 90 percent of these estimated values. The upper bound, $\overline{K}(d)$, of this interval is given by the 95th percentile of the counterfactual distribution, and the lower bounds, $\underline{K}(d)$, by the 5th percentile of that distribution. We construct only *global* confidence bands such that deviations by randomly generated K-densities are equally likely across all levels of distances (see Duranton and Overman, 2005, for details).

Fourth step (identification of location patterns). Industries whose observed K-densities fall into their confidence band could be 'as good as random' and are, therefore, not considered to be either localized or dispersed. Any deviation from the confidence band constructed in the third step indicates localization or dispersion of the industry. If $\widehat{K}(d) > \overline{K}(d)$ for at least one $d \in [0, x]$, whereas it never lies below $\underline{K}(d)$ for all $d \in [0, x]$, industry A is said to be globally localized at the 5 percent confidence level. On the other hand, if $\widehat{K}(d) < \underline{K}(d)$ for at least one $d \in [0, x]$, industry A is said to be globally dispersed.[7] We can also define an index of global

[7] Barlet, Briant, and Crusson (2013, p.345) show that "the DO test for localization suffers from a systematic upward bias in small samples, and, more importantly, that this bias increases with the number of plants in the

localization, $\gamma_i(d) \equiv \max\{\widehat{K}(d) - \overline{K}(d), 0\}$, as well as an index of global dispersion:

$$\psi_i(d) \equiv \begin{cases} \max\{\underline{K}(d) - \widehat{K}(d), 0\} & \text{if} \quad \sum_{d=0}^{x} \gamma_i(d) = 0 \\ 0 & \text{otherwise.} \end{cases}$$

The strength of localization and dispersion up to some distance $\overline{d} \leq x$ can be measured by:

$$\mathit{\Gamma}_i(\overline{d}) \equiv \sum_{d=0}^{\overline{d}} \gamma_i(d) \quad \text{and} \quad \mathit{\Psi}_i(\overline{d}) \equiv \sum_{d=0}^{\overline{d}} \psi_i(d), \tag{3}$$

which corresponds to the integral between the observed distribution and the upper- and lower-bounds of the confidence band. These two measures capture how 'strongly' an industry deviates from randomness. Of course, $\mathit{\Gamma}_i = \mathit{\Psi}_i = 0$ for all distances for industries that do not deviate significantly from randomness.

Implementation details. We first need to determine over what distance range x we compute the K-densities. In our application, we consider a range of distances between zero and 1,000 kilometers. Since Russia is a large country, it is important to evaluate the K-densities over a sufficiently long range. However, the computational burden increases substantially with the number of points on which we evaluate the K-densities. We believe that 1,000 kilometers strikes the right balance between the need for longer distances, the geographic structure of Russia, and the computation time.[8] Furthermore, we need to determine the step size between two successive distances for evaluating the K-density. There is again a tradeoff between using a fine grid (many points) and the computational burden. We use three different criteria, depending on the sample sizes (small, medium, or large). We compute the K-densities successively using step sizes of: 1 kilometer for the small sample; 5 kilometers for the medium sample; and 10 kilometers for the large sample. With step sizes of 5 or 10 kilometers, we use the interpolated value $[\widehat{K}(d) + \widehat{K}(d + \text{step size})] \times (\text{step size}/2)$ in the computations of the CDF. We do the same to compute $\gamma_i(d)$ and $\psi_i(d)$.

3.2 Agglomeration: Results

As explained before, we estimate the K-densities separately for our large, medium, and small samples; and for the whole of Russia, the western part of Russia, and the eastern part of

industry." We acknowledge this problem but do not think that this changes systematically the results of our subsequent analysis.

[8] Behrens and Bougna (2015) use 800 kilometers for Canada, which is also a large country. In Canada, most distances between neighboring large cities fall into that distance range. The same is true for Russia using a 1,000 kilometers cutoff. Observe that we did not use the algorithm with discrete binning proposed by Scholl and Brenner (2015), which speeds up the computations substantially. We did our computations before knowing about this new procedure. All our computations are carried our for the 'exact' K-densities, including our computations of coagglomeration measures.

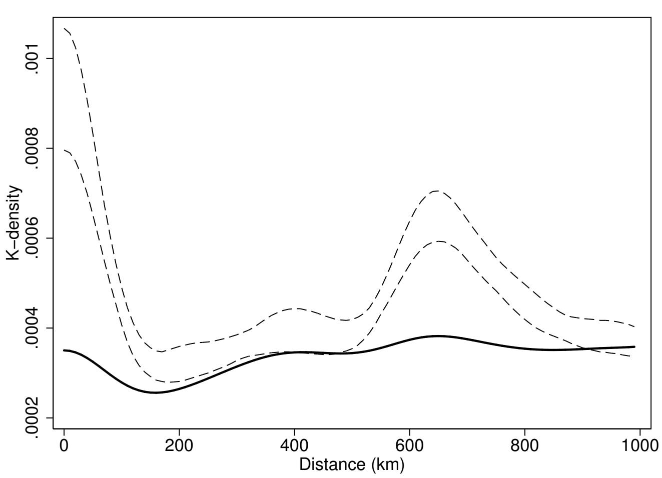
Russia. The estimations are carried out at the industry level for 103 3-digit industries, and 296 4-digit industries, respectively. We consider that the 3-digit results are more precise because plants were not legally compelled to provide more detailed industry codes before 2014. We nevertheless report 4-digit results for the sake of completeness and since they are interesting on their own. For each industry and sample, we also compute global confidence bands based on 1,000 random permutations as explained before.

3.2.1 Results for all of Russia

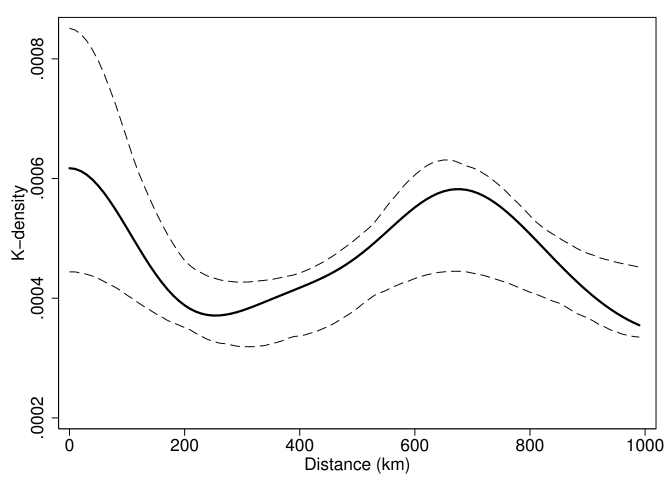
We first report estimation results for all of Russia. We present figures for the large sample only in the main text. Details on how the results compare between the large, the medium, and the small samples are relegated to the supplemental Appendix S.1. Overall, the results are fairly similar across the different samples, though some industries switch between agglomeration and randomness or between randomness and dispersion.

Figure 3: K-density estimations for selected OKVED 3-digit industries (all of Russia, large sample).

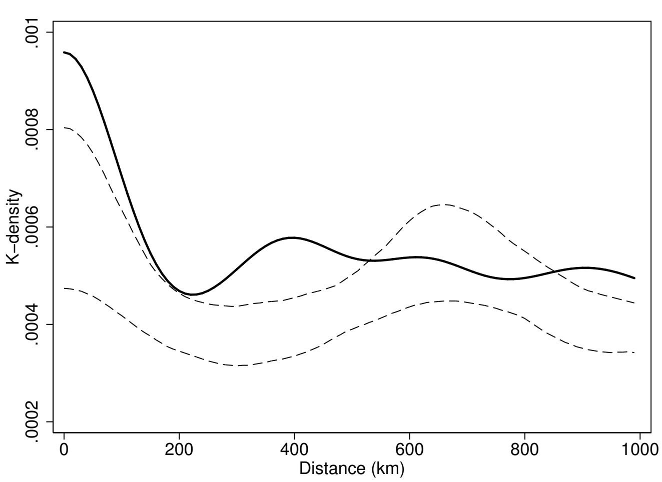
(1) Manufacture of beverages.



(2) Cast iron and steel other primary processing.



(3) Manufacture of motor vehicles.



(4) Weaving manufacture.

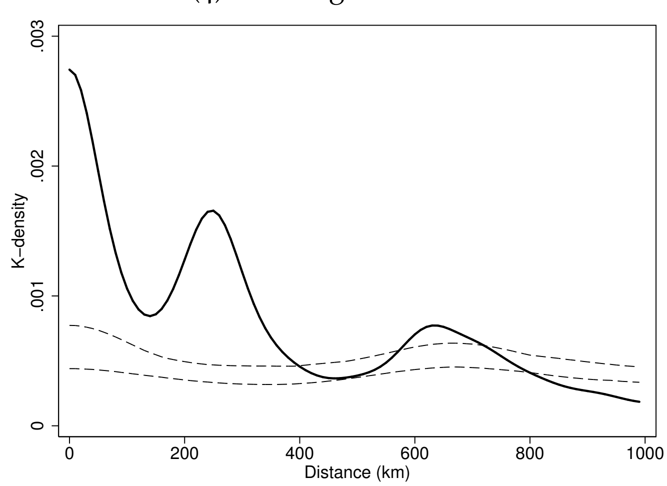


Figure 3 illustrates examples of the K-densities and confidence bands for four different location patterns of 3-digit industries computed using the large sample. First, 'Manufacture of beverages' (OKVED 159) in panel (1) of Figure 3 is significantly less localized than manufacturing in general. This industry is hence geographically more dispersed than overall manufacturing activity. Second, 'Cast iron and steel other primary processing' (OKVED 273) in panel (2) is neither localized nor dispersed. It closely follows the overall location pattern of manufacturing in Russia and can, therefore, not be distinguished from an industry that would locate randomly. Third, 'Manufacture of motor vehicles' (OKVED 341) in panel (3) is significantly more localized than manufacturing in general, especially at short distances, at distances of about 400 kilometers, and at longer distances. However, that industry is not jointly overrepresented in the Moscow and Saint-Petersburg regions, as can be seen from its K-density at about 600-800 kilometers, which corresponds to the distance between these two major metropolitan areas. Last, 'Weaving manufacture' (OKVED 172) in panel (4) is the most strongly localized industry in our example, especially at short geographic distances, and at distances of about 200 kilometers. That industry is also jointly overrepresented in the Moscow and Saint-Petersburg regions, as seen from the peak at around 650–700 kilometers.

Table 1 summarizes the agglomeration and dispersion patterns of industries for all of Russia, the western part, and the eastern part. We report a full set of results for 3- and 4-digit industries, and for our three different sample sizes. As panel (a) of Table 1 shows, about 42%–52% of 4-digit industries are significantly localized for all of Russia, whereas the corresponding figures for 3-digit industries are about 63%–75%. For our preferred sample—the large one—about half of the 4-digit industries and three-quarter of the 3-digit industries are localized for all of Russia; about 30% of 4-digit industries and 10% of 3-digit industries are as good as random; and 15-20% of 3- and 4-digit industries are significantly dispersed. There is hence substantial localization, especially at a higher level of industrial aggregation.

Comparing our results to those for Canada—another geographically large country—we find that manufacturing industries in Russia are more strongly localized. Behrens and Bougna (2015) report results for 6- and 4-digit manufacturing industries (259 and 86 industries using the North American Industrial Classification, NAICS, respectively), and find that the share of localized industries is about 10 to 15 percentage points lower. One possible explanation might be that Russia has a much larger population and many more large cities than Canada. Indeed, the Canadian figures for geographic concentration resemble more those observed in the eastern part of Russia, which has fewer large cities, than those in the western part. Another possible explanation is that the geographic concentration patterns we observe nowadays go back to the planned economy of the USSR and are remains from the past where state intervention largely pinned down the location of industries.

Tables 2 and 3 shows how geographic concentration patterns differ systematically across broad industry groups. The top panel lists the 2-digit industries that contain the largest shares

Table 1: Summary of geographic concentration patterns for Russian manufacturing industries.

	(a) All of Russia				(b) Western Russia				(c) Eastern Russia			
	OKVED 4-digit		OKVED 3-digit		OKVED 4-digit		OKVED 3-digit		OKVED 4-digit		OKVED 3-digit	
Status	Number	Percentage	Number	Percentage	Number	Percentage	Number	Percentage	Number	Percentage	Number	Percentage
	Small sample ($N = 178,138$)											
Localized	125	42%	65	63%	143	48%	71	69%	73	28%	40	39%
Random	120	41%	15	15%	119	40%	18	17%	178	68%	56	54%
Dispersed	51	17%	23	22%	34	11%	14	14%	12	5%	7	7%
Total	296	100%	103	100%	296	100%	103	100%	263	100%	103	100%
$\overline{\Gamma}\|_{\Gamma_i>0}$	0.078		0.061		0.071		0.055		0.070		0.052	
$\overline{\Psi}\|_{\Psi_i>0}$	0.020		0.024		0.020		0.029		0.016		0.022	
	Medium sample ($N = 256,943$)											
Localized	147	50%	73	71%	162	55%	79	77%	95	35%	50	49%
Random	98	33%	14	14%	99	33%	14	14%	164	60%	45	44%
Dispersed	51	17%	16	16%	35	12%	10	10%	14	5%	8	8%
Total	296	100%	103	100%	296	100%	103	100%	273	100%	103	100%
$\overline{\Gamma}\|_{\Gamma_i>0}$	0.075		0.061		0.073		0.058		0.063		0.048	
$\overline{\Psi}\|_{\Psi_i>0}$	0.023		0.029		0.020		0.031		0.018		0.022	
	Large sample ($N = 319,684$)											
Localized	154	52%	77	75%	177	60%	83	81%	107	38%	54	52%
Random	87	29%	10	10%	80	27%	12	12%	159	57%	43	42%
Dispersed	55	19%	16	16%	39	13%	8	8%	13	5%	6	6%
Total	296	100%	103	100%	296	100%	103	100%	279	100%	103	100%
$\overline{\Gamma}\|_{\Gamma_i>0}$	0.071		0.058		0.067		0.056		0.065		0.050	
$\overline{\Psi}\|_{\Psi_i>0}$	0.025		0.035		0.021		0.034		0.014		0.031	

Notes: All K-densities are computed for a range of 0–1000 kilometers for 103 3-digit and 296 4-digit OKVED industries. Some 4-digit industries are not present in the eastern part of Russia, which explains the smaller number of industries in some computations. The confidence bands are computed using 1,000 bootstrap replications. We compute the K-densities in 1, 5, and 10 kilometers steps for the small, the medium, and the large samples, respectively. See Figure 1 and Appendix A.2 for details on how we split Russia into a western and an eastern part. The values of $\overline{\Gamma}|_{\Gamma_i>0}$ and $\overline{\Psi}|_{\Psi_i>0}$ are computed at the last point at which the K-densities are evaluated for each sample (990km in the large, 995km in the medium, and 999km in the small sample, respectively). We report average values for all significantly localized industries in the case of $\overline{\Gamma}|_{\Gamma_i>0}$, and for all significantly dispersed industries in the case of $\overline{\Psi}|_{\Psi_i>0}$.

Table 2: Localization patterns of OKVED 4-digit industries by broad industry groups (all of Russia).

			Small sample				**Medium sample**				**Large sample**			
OKVED2 ind.	Industry name	OKVED4 subind.	# local.	# rand.	# disp.	% local.	# local.	# rand.	# disp.	% local.	# local.	# rand.	# disp.	% local.
			Strong localization patterns											
19	Manufacturing of leather; leather articlles and manufacture of footwear	3	3	0	0	100	3	0	0	100.00	3	0	0	100.00
32	Manufacture of radio, television and communication electronic components and apparatus	3	3	0	0	100	3	0	0	100.00	3	0	0	100.00
30	Manufacture of office machinery and computers	3	3	0	0	100	3	0	0	100.00	3	0	0	100.00
18	Manufacture of wearing apparel; dressing and dyeing of fur	7	6	1	0	85.71	7	0	0	100.00	6	0	1	85.71
33	Manufacture of medical instruments, measure, control and test devices, optical devices, photo and cine equipment, watches	5	4	0	1	80	4	0	1	80.00	4	0	1	80.00
31	Manufacture of electrical machinery and apparatus	9	7	0	2	77.78	8	0	1	88.89	8	0	1	88.89
17	Textile manufacture	24	18	6	0	75	19	5	0	79.17	18	5	1	75.00
22	Publishing, printing and reproduction of recorded media	16	12	2	2	75	14	1	1	87.50	13	1	2	81.25
			Intermediate localization patterns											
34	Manufacture of motor vehicles, trailers and semi-trailers	3	2	1	0	66.67	2	1	0	66.67	2	1	0	66.67
20	Woodworking and manufacture of wood and cork articles, except furniture	7	4	2	1	57.14	5	2	0	71.43	5	2	0	71.43
21	Manufacture of cellulose, pulp, paper, cardboard and articles of these materials	9	5	4	0	55.55	5	4	0	55.56	5	4	0	55.56
24	Manufacture of chemicals and chemical products	24	11	12	1	45.83	14	8	2	58.33	17	5	2	70.83
25	Manufacture of rubber and plastic products	9	4	4	1	44.44	6	3	0	66.67	6	3	0	66.67
			Weak localization patterns											
36	Manufacture of furniture	16	7	6	3	43.75	7	5	4	43.75	9	3	4	56.25
29	Manufacture of machinery and equipment	29	12	13	4	41.38	13	11	5	44.83	14	10	5	48.28
28	Manufacture of fabricated metal products	21	7	9	5	33.33	11	4	6	52.38	12	3	6	57.14
27	Manufacture of basic metals	20	5	14	1	25	3	15	2	15.00	4	13	3	20.00
35	Manufacture of ships, aircaft and spacecraft and other transport	10	2	7	1	20	2	6	2	20.00	2	5	3	20.00
26	Manufacture of other non-metallic mineral products	31	5	17	9	16.13	6	16	9	19.35	7	14	10	22.58
15	Manufacture of food products and beverages	41	5	19	17	12.19	10	14	17	24.39	11	15	15	26.83
37	Recycling of secondary raw materials	2	0	0	2	0	1	0	1	50.00	1	0	1	50.00
23	Manufacture of coke, refined petroleum products and nuclear fuel	3	0	2	1	0	1	2	0	33.33	1	2	0	33.33
16	Manufacture of tobacco products	1	0	1	0	0	0	1	0	0.00	0	1	0	0.00

Notes: This table reports the localization status of all OKVED 4-digit industries within the same 2-digit industry. We report 2-digit industries by broad localization patterns ('Strong localization patterns', 'Intermediate localization patterns', and 'Weak localization patterns') based on the frequency of localization of the 4-digit industries that make up the 2-digit industry.

Table 3: Localization patterns of OKVED 3-digit industries by broad industry groups (all of Russia).

			Small sample				**Medium sample**				**Large sample**			
OKVED2 ind.	Industry name	OKVED3 subind.	# local.	# rand.	# disp.	% local.	# local.	# rand.	# disp.	% local.	# local.	# rand.	# disp.	% local.
			Strong localization patterns											
17	Textile manufacture	7	7	0	0	100.00	7	0	0	100.00	7	0	0	100.00
19	Manufacturing of leather; leather articlles and manufacture of footwear	3	3	0	0	100.00	3	0	0	100.00	3	0	0	100.00
21	Manufacture of cellulose, pulp, paper, cardboard and articles of these materials	2	2	0	0	100.00	2	0	0	100.00	2	0	0	100.00
22	Publishing, printing and reproduction of recorded media	3	3	0	0	100.00	3	0	0	100.00	3	0	0	100.00
30	Manufacture of office machinery and computers	1	1	0	0	100.00	1	0	0	100.00	1	0	0	100.00
32	Manufacture of radio, television and communication electronic components and apparatus	3	3	0	0	100.00	3	0	0	100.00	3	0	0	100.00
29	Manufacture of machinery and equipment	7	6	1	0	85.71	6	1	0	85.71	6	1	0	85.71
36	Manufacture of furniture; manufacturing	6	5	0	1	83.33	6	0	0	100.00	6	0	0	100.00
31	Manufacture of electrical machinery and apparatus n	6	5	0	1	83.33	5	0	1	83.33	5	0	1	83.33
20	Woodworking and manufacture of wood and cork articles, except furniture	5	4	0	1	80.00	4	1	0	80.00	4	0	1	80.00
			Intermediate localization patterns											
24	Manufacture of chemicals and chemical products	7	5	2	0	71.43	4	3	0	57.14	6	1	0	85.71
34	Manufacture of motor vehicles, trailers and semi-trailers	3	2	1	0	66.67	2	1	0	66.67	2	1	0	66.67
18	Manufacture of wearing apparel; dressing and dyeing of fur	3	2	1	0	66.67	2	0	1	66.67	3	0	0	100.00
33	Manufacture of medical instruments, measure, control and test devices, optical devices, photo and cine equipment, watches	5	3	0	2	60.00	4	0	1	80.00	4	0	1	80.00
28	Manufacture of fabricated metal products	7	4	0	3	57.14	5	0	2	71.43	5	0	2	71.43
25	Manufacture of rubber and plastic products	2	1	1	0	50.00	2	0	0	100.00	2	0	0	100.00
			Weak localization patterns											
27	Manufacture of basic metals	5	2	3	0	40.00	3	2	0	60.00	3	2	0	60.00
35	Manufacture of ships, aircaft and spacecraft and other transport	5	2	2	1	40.00	3	2	0	60.00	3	1	1	60.00
15	Manufacture of food products and beverages	9	3	0	6	33.33	3	0	6	33.33	4	0	5	44.44
26	Manufacture of other non-metallic mineral products	8	2	1	5	25.00	3	1	4	37.50	3	1	4	37.50
23	Manufacture of coke, refined petroleum products and nuclear fuel	3	0	2	1	0.00	1	2	0	33.33	1	2	0	33.33
37	Recycling of secondary raw materials	2	0	0	2	0.00	1	0	1	50.00	1	0	1	50.00
16	Manufacture of tobacco products	1	0	1	0	0.00	0	1	0	0.00	0	1	0	0.00

Notes: This table reports the localization status of all OKVED 3-digit industries within the same 2-digit industry. We report 2-digit industries by broad localization patterns ('Strong localization patterns', 'Intermediate localization patterns', and 'Weak localization patterns') based on the frequency of localization of the 3-digit industries that make up the 2-digit industry.

of localized 4-digit (Table 2) and 3-digit (Table 3) industries, respectively. As can be seen from Table 2, the most localized industry groups include textile and leather (OKVED 17–19), different types of electric machinery and electronic equipment and devices (OKVED 30–33), and printing and publishing (OKVED 22). Industry types with intermediate localization patterns include wood, paper, chemicals, and plastic (OKVED 20–21 and 23–24), as well as motor vehicle manufacturing (OKVED 34). Finally, the least localized industry groups are related to furniture, different types of metal products, non-metallic mineral products, food, and raw material processing industries. These rankings are fairly stable across our samples of different sizes.

As Table 3 shows, the basic patterns are very similar when looking at 3-digit industries, where textiles, machinery, and publishing and printing are among the industry types displaying strong localization patterns, whereas basic metals, food and beverages, non-metallic mineral products and raw material processing industries have the weakest localization patterns. The only notable changes between Tables 2 and 3 are the paper and wood industries that appear more localized when looking at their 3-digit components than their 4-digit components, whereas some industries related to machinery and medical devices appear less localized. These differences are driven by the different ways in which the 4-digit subgroups relate to each other within the 3-digit groups. Overall, however, the picture is very consistent, both across industry definitions (3- or 4-digit) and sample sizes.

Comparing again these results with those by Behrens and Bougna (2015, Table 7) for Canada, we find that there is a very substantial overlap. In Canada, the industry groups that are among the most geographically localized include 'Clothing Manufacturing', 'Textile Mills', 'Machinery Manufacturing', and 'Printing and Related Support Activities'; whereas those among the most dispersed include 'Petroleum and Coal Products Manufacturing', 'Food Manufacturing', 'Beverage and Tobacco Product Manufacturing', and 'Non-Metallic Mineral Product Manufacturing'. Clearly, the overall pattern is very similar.

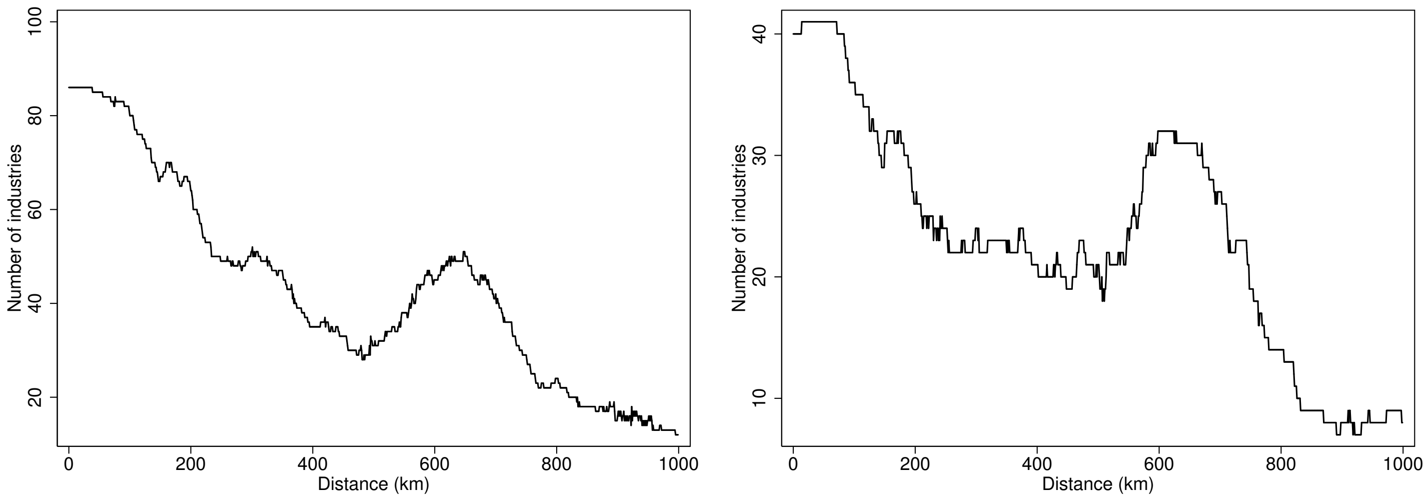
Figure 4 depicts the number of significantly localized industries by distance.[9] As shown, the localization patterns are fairly similar across the different samples and the different levels of industrial aggregation. There is a large number of significantly localized industries at short distances of about 50–100 kilometers, and localization then falls off rapidly. It rises and peaks again at about 650–700 kilometers, which is the distance between the two major economic centers of the country, the federal cities of Moscow and Saint Petersburg. This suggests that, as in Canada (see Behrens and Bougna, 2015), industries tend to cluster at short distances and also between major economic centers. As we will show later using the coagglomeration patterns between industry pairs, the major economic centers still display a substantial degree of industrial specialization, i.e., they host also a share of mutually exclusive industries.

[9] Recall that—to reduce the computational burden—we estimate the K-densities for the small sample with step 1 kilometer, whereas the steps are 5 and 10 kilometers for the medium and the large samples, respectively. The different step sizes explain why panel (1) of Figure 4 is less 'smooth' than the other two panels.

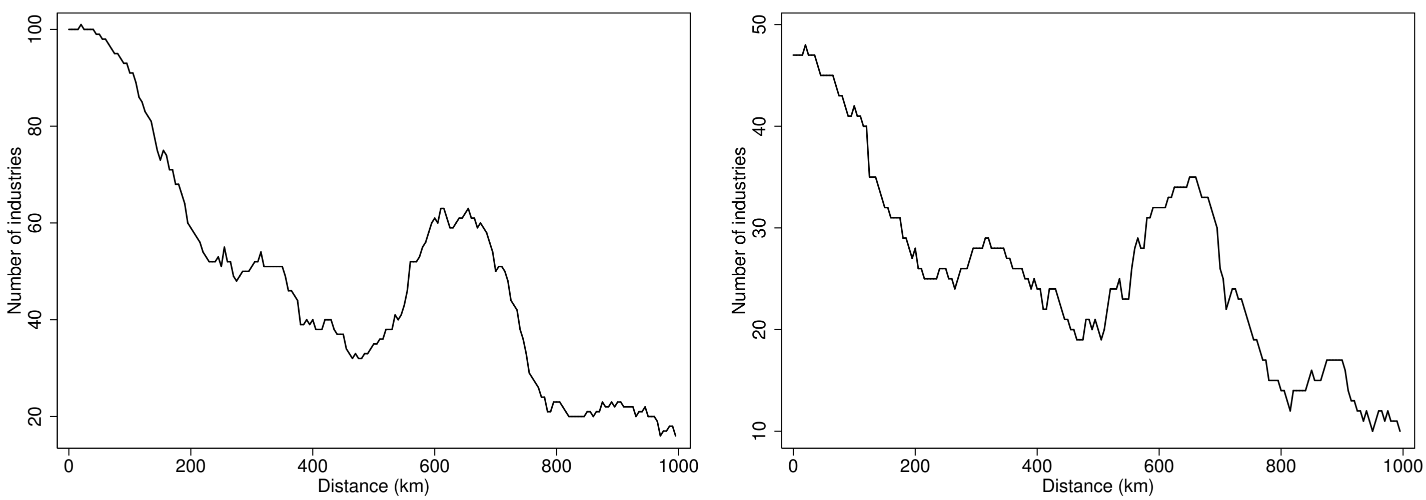
Figure 4: Number of significantly localized industries by distance (all of Russia).

(a) OKVED 4-digit. (b) OKVED 3-digit.

(1) Small sample.



(2) Medium sample.



(3) Large sample.

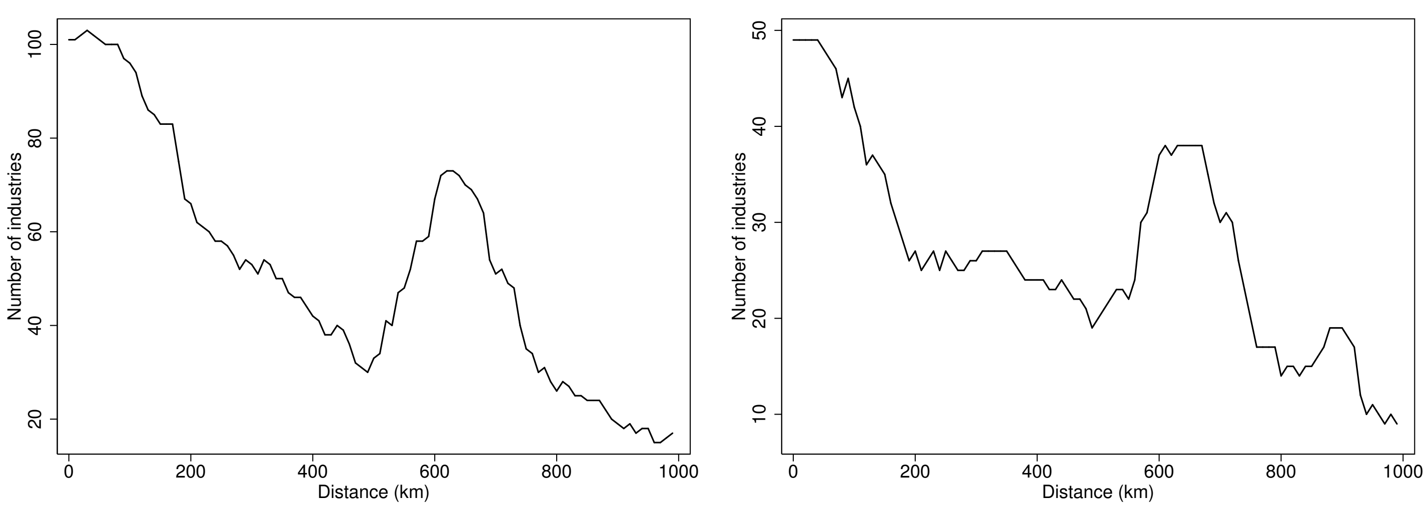
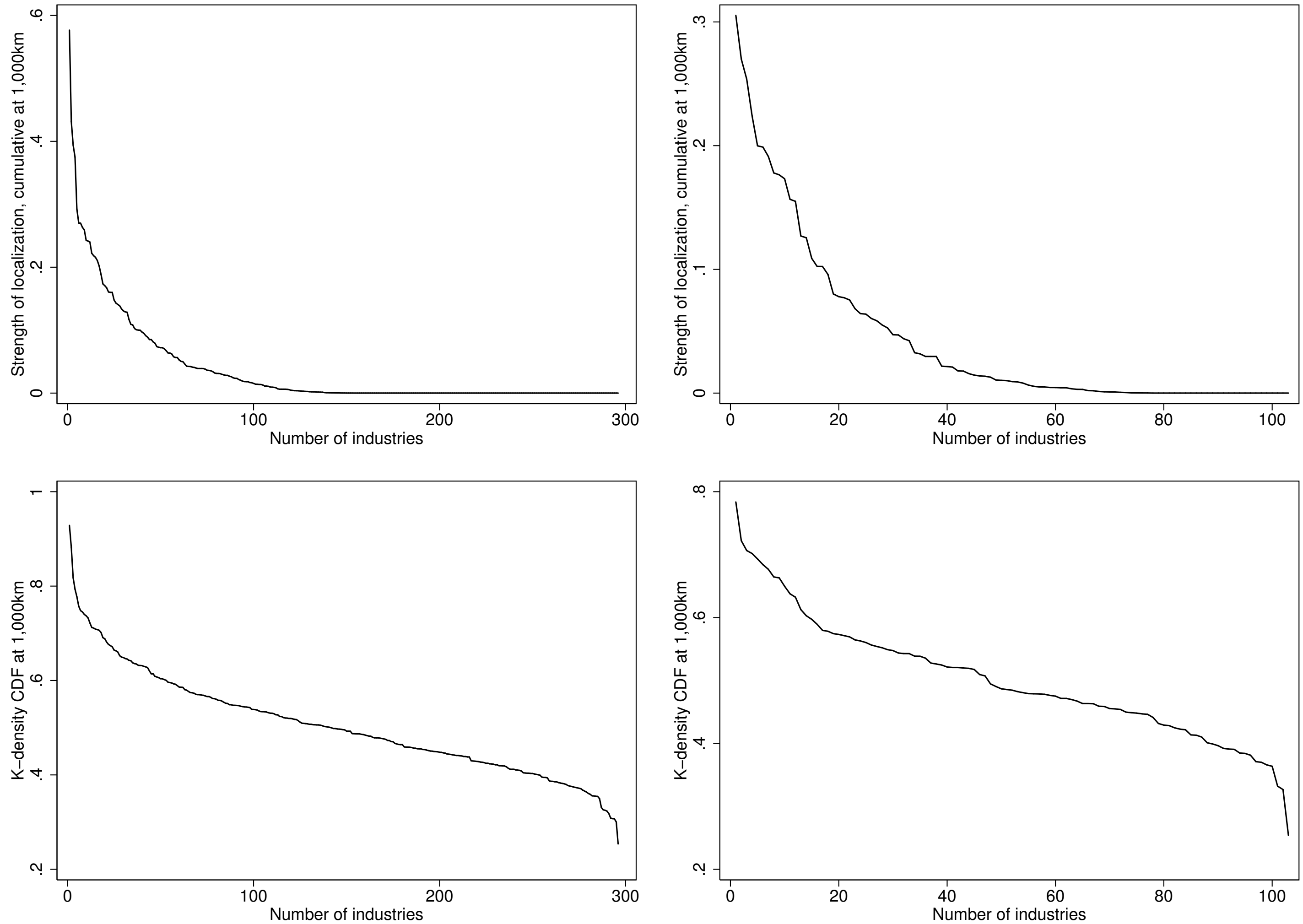


Figure 5: Skewness of the strength of localization and K-density CDF (all of Russia, large sample).

(a) OKVED 4-digit. (b) OKVED 3-digit.



Panel (a) of Figure 5 shows that there are a few highly localized 4-digit industries, whereas most industries are not strongly localized. Panel (b) shows that the patterns at the 3-digit level are similar but less extreme. Hence, very strong localization patterns tend to occur for narrowly defined industries, whereas most industries do not display very strong patterns of localization. The bottom two panels of Figure 5 also show that the patterns are less skewed when considering the K-density CDFs instead of the strength of localization. When taken together, these two results suggest that there is substantial localization of some industries in excess of the overall level of geographic concentration of manufacturing.

Which individual industries are the most strongly localized compared to manufacturing in general? And which industries are the most strongly agglomerated? Tables 4 and 5 list the top ten most localized and most agglomerated 4-digit manufacturing industries in Russia, respectively (Tables 18 and 19 in the supplemental Appendix S.2 present the same results for the 3-digit industries). As can be seen from Table 4, textile-related industries, publishing, non-metallic mineral products, pharmaceuticals, and aircraft and spacecraft rank among the most localized industries. These patterns are similar to those in Table 5, thus suggesting that the most strongly localized industries are also those that are the most agglomerated. Observe that the strong geographic concentration of textile- and clothing-related industries has been documented before for high-income countries like the U.K. (Duranton and Overman, 2005), the US (Ellison, Glaeser, and Kerr, 2010), Japan (Nakajima, Saito, and Uesugi, 2013), Canada (Behrens and Bougna, 2015; Behrens, Boualam, and Martin, 2017), Germany (Riedel and Koh, 2014), and France (Barlet et al., 2013). Our results show that we also observe that concentration for middle-income countries like Russia, which suggests that agglomeration forces pushing towards geographic concentration are especially strong for those industries and do not depend substantially on the level of economic development.

3.2.2 Results for eastern and western Russia

As explained before, Russia is a large country with a dense western part and a more sparsely populated eastern part separated by the Ural mountains. To account for 'dual geographi structure', we now report separate estimation results for these two parts of Russia. To save space, we present figures for the large sample only in the main text and relegate additional results to the supplemental Appendix S.2.

First, as shown by panels (b) and (c) of Table 1, geographic concentration patterns are stronger in the western part of Russia (48–60% of localized 4-digit industries, and 69–81% of localized 3-digit industries) than in the eastern part (28%–38% of localized 4-digit industries, and 39–52% of localized 3-digit industries). The western part of Russia has more pronounced geographic location patterns, whereas the eastern part has a larger share of industries that are as good as randomly located.

Figure 7 shows the strength of localization for western Russia (panel (1)) and for eastern Russia (panel (2)). This figure confirms that the overall degree of geographic concentration is stronger in the west than in the east. Yet, the distributions look quite similar in both regions: there are only a few strongly localized industries, whereas most industries display less extreme geographic patterns. The results are similar for the 3-digit industries (see Figure 15 in the supplemental Appendix S.2). Finally, Tables 6 and 7 summarize the most strongly localized and geographically most agglomerated industries in the east and the west. While different kinds of publishing and recording, metal, and pharmaceutical industries make the list in the west, the industries in the east are different, including cutlery, ships, and motor vehicles. These differences can be linked to different broad specialization patterns and to different concentration patterns in the less dense east of Russia. Additional results—including the localization and dispersion patterns at the 3-digit level for the east and the west, as well as results at the 4-digit

Table 4: Top-10 *most localized* industries (all of Russia, OKVED 4-digit).

OKVED	Industry name	# of plants	Γ_A
Small sample			
2232	Reproduction of video recording	55	0.701
2600	Manufacture of other non-metallic mineral products	94	0.573
1721	Cotton-type weaving	151	0.350
2231	Reproduction of sound recording	76	0.314
1711	Spinning of cotton-type fibres	65	0.305
1760	Manufacture of textile fabrics	61	0.275
2441	Manufacture of basic pharmaceutical products	296	0.269
1715	Manufacture of silk, synthetic and artificial fibres	24	0.268
2440	Manufacture of pharmaceuticals	325	0.259
2215	Other publishing	902	0.253
Medium sample			
2232	Reproduction of video recording	67	0.654
2600	Manufacture of other non-metallic mineral products	131	0.609
1721	Cotton-type weaving	227	0.449
1715	Manufacture of silk, synthetic and artificial fibres	32	0.351
2231	Reproduction of sound recording	112	0.346
2214	Publishing of sound recordings	331	0.329
2441	Manufacture of basic pharmaceutical products	414	0.287
1720	Weaving manufacture	163	0.272
2215	Other publishing	1,259	0.264
3530	Manufacture of aircraft and spacecraft	707	0.262
Large sample			
2600	Manufacture of other non-metallic mineral products	141	0.577
1721	Cotton-type weaving	267	0.432
1715	Manufacture of silk, synthetic and artificial fibres	43	0.394
2214	Publishing of sound recordings	430	0.375
2441	Manufacture of basic pharmaceutical products	498	0.292
1720	Weaving manufacture	210	0.270
3530	Manufacture of aircraft and spacecraft	817	0.270
2231	Reproduction of sound recording	134	0.263
2215	Other publishing	1,581	0.259
1711	Spinning of cotton-type fibres	105	0.243

Notes: Γ_A is computed at 990km, 995km and 999km (the last point at which the K-densities are evaluated) for the large, the medium, and the small samples, respectively. We hence measure localization over the whole distance range that we compute the K-densities for.

level—are given in the supplemental Appendix S.2 (see Tables 20, 21, 22, 23, 24, and 25).

3.3 Coagglomeration: Methodology

Until now, we have only investigated the agglomeration patterns of individual industries. However, recent research on the determinants of agglomeration and clusters has emphasized that the *coagglomeration patterns of industry pairs* convey valuable information as to the underlying agglomeration mechanisms (see Ellison et al., 2010; Behrens, 2016; Faggio, Silva, and Strange, 2017). We hence now compute the coagglomeration patterns for Russian manufacturing industry pairs. For computational reasons, we only do so for the OKVED 3-digit industries—

Table 5: Top-10 *most geographically concentrated* industries (all of Russia, OKVED 4-digit).

OKVED	Industry name	# of plants	CDF
Small sample			
2232	Reproduction of video recording	55	0.544
2600	Manufacture of other non-metallic mineral products	94	0.506
2211	Publishing of books	2,743	0.207
2231	Reproduction of sound recording	76	0.206
2215	Other publishing	902	0.189
1716	Manufacture of sewing threads	7	0.165
1722	Woollen-type weaving	14	0.158
2441	Manufacture of basic pharmaceutical products	296	0.148
2440	Manufacture of pharmaceuticals	325	0.147
2210	Publishing	5,413	0.140
Medium sample			
2600	Manufacture of other non-metallic mineral products	131	0.511
2232	Reproduction of video recording	67	0.509
2231	Reproduction of sound recording	112	0.234
2214	Publishing of sound recordings	331	0.224
2211	Publishing of books	3,676	0.216
2215	Other publishing	1,259	0.208
3530	Manufacture of aircraft and spacecraft	707	0.168
2441	Manufacture of basic pharmaceutical products	414	0.167
1721	Cotton-type weaving	227	0.163
2210	Publishing	7,831	0.159
Large sample			
2600	Manufacture of other non-metallic mineral products	141	0.499
2214	Publishing of sound recordings	430	0.283
2211	Publishing of books	4,573	0.227
2215	Other publishing	1,581	0.219
2441	Manufacture of basic pharmaceutical products	498	0.183
3530	Manufacture of aircraft and spacecraft	817	0.177
2210	Publishing	10,088	0.168
1721	Cotton-type weaving	267	0.166
2231	Reproduction of sound recording	134	0.163
2440	Manufacture of pharmaceuticals	537	0.160

Notes: We report the CDF of the K-density at a distance of $d = 50$km. Hence, the values summarize the share of bilateral distances between pairs of establishments in the industry that is below 50 kilometers.

103 industries, for a total of $(103 \times 102)/2 = 5,253$ unique industry pairs—using the medium-sized samples for all of Russia with 5 kilometers steps.[10] As shown by Duranton and Overman (2008), their methodology can be readily adapted to assess the coagglomeration of two different industries. As for the case of single industries in Section 3.1, we again estimate K-densities for the distribution of bilateral distances between manufacturing establishments. However, we now restrict these densities to pairs of establishments *in different industries*.

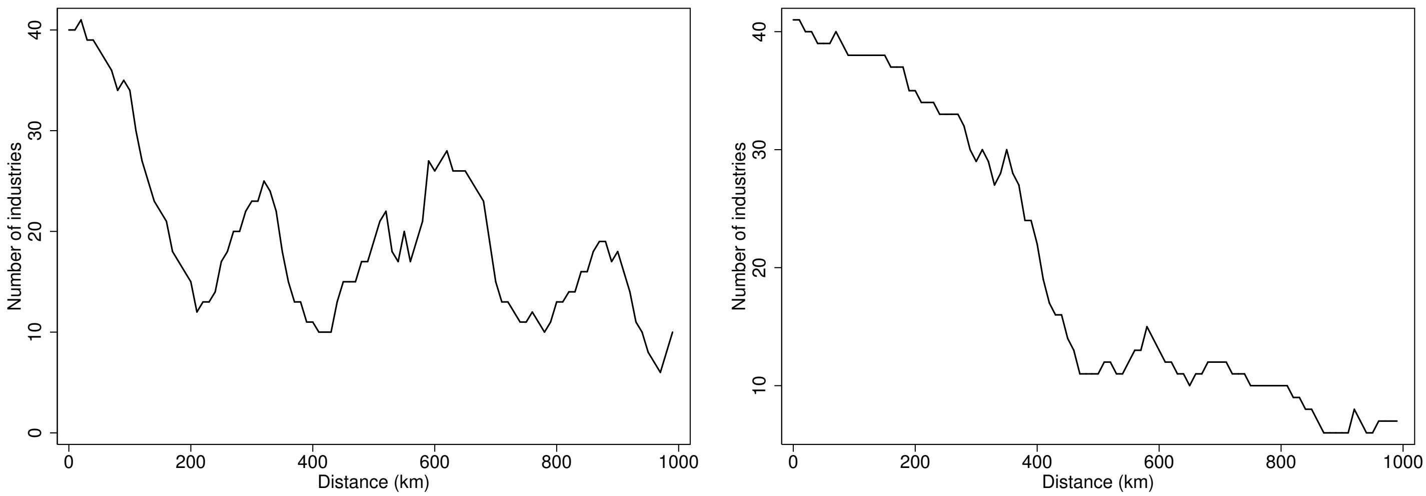
Formally, consider two industries A and B with n_A and n_B plants, respectively. There are

[10] As shown before, the large samples yield qualitatively similar results, yet using the large samples is too heavy a computational burden as it involves too many industry pairs with too many establishments. Furthermore, at the 4-digit level we just have too many industry pairs, namely $(296 \times 295)/2 = 43,660$ unique pairs.

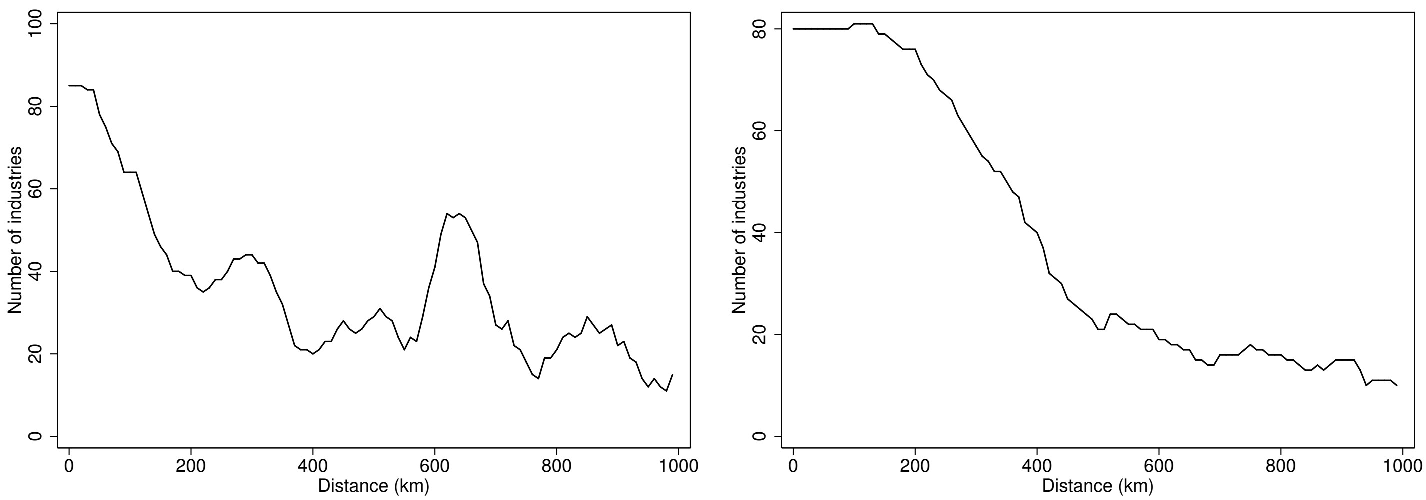
Figure 6: Agglomeration of industries by distance (western and eastern parts of Russia).

(a) Western Russia. (b) Eastern Russia.

(1) OKVED 3-digit, large sample.



(2) OKVED 4-digit, large sample.



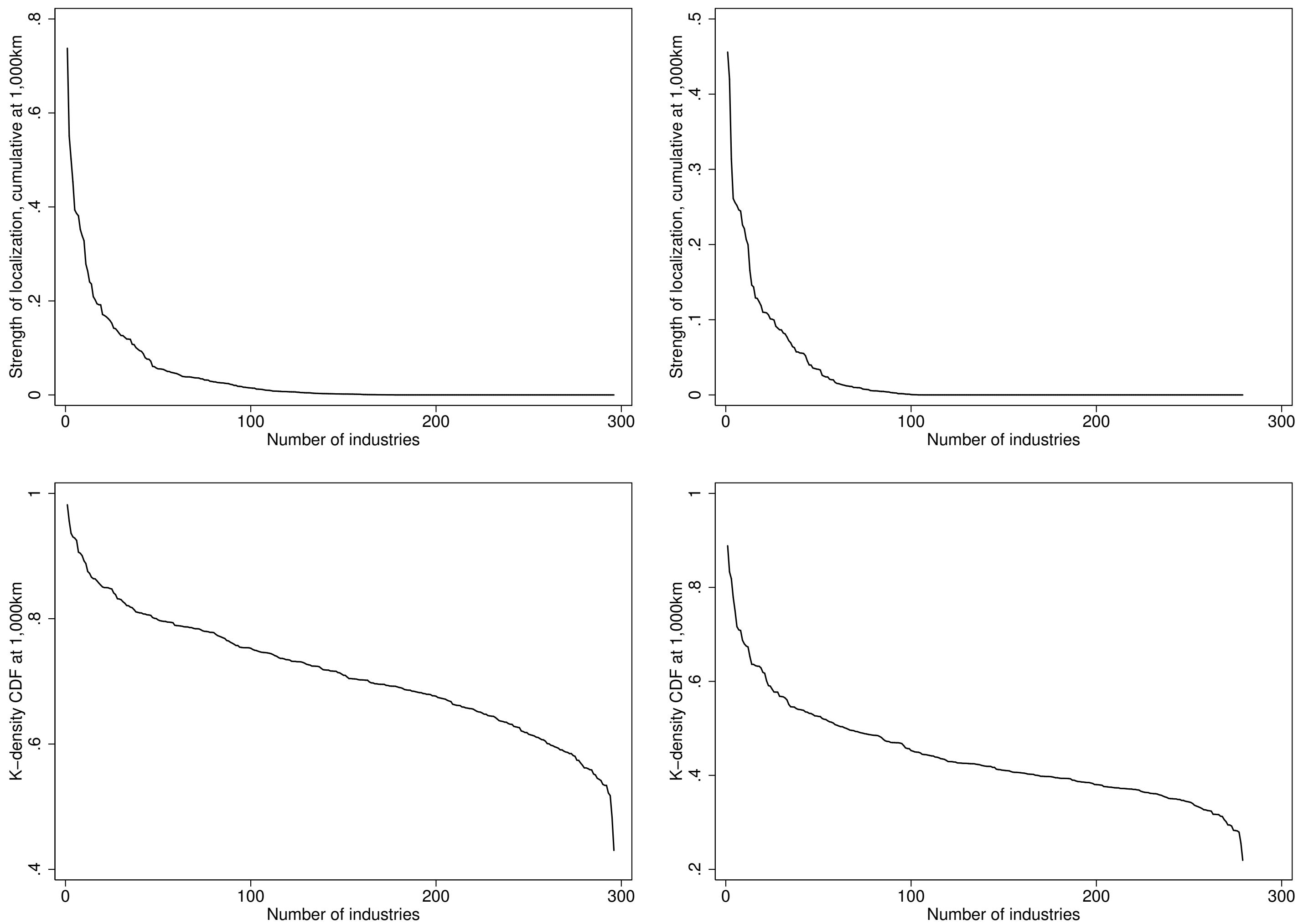
$n_A \times n_B$ unique bilateral distances between all pairs of plants in the two industries. Hence, analogously to (1), the kernel-smoothed estimator of the density of these pairwise distances at distance d is:

$$\widehat{K}_c(d) = \frac{1}{n_A n_B h} \sum_{i=1}^{n_A} \sum_{j=1}^{n_B} f\left(\frac{d - d_{ij}}{h}\right), \tag{4}$$

where h is the optimal bandwidth—set using Silverman's rule of thumb—and $f(\cdot)$ is a Gaussian kernel function. We again estimate expression (4) for all $d \leq x$, where x is the cutoff distance of 1,000 kilometers. The K-density (4) gives the distribution of bilateral distances between establishments in the two industries.

Figure 7: Skewness of the strength of localization and K-density CDF (large sample, OKVED 4-digit).

(1) Western Russia. (2) Eastern Russia.



As before, its CDF up to some distance $\overline{d} \leq x$ is:

$$\mathrm{CDF}_c(\overline{d}) = \sum_{d=0}^{\overline{d}} \widehat{K}_c(d), \tag{5}$$

which measures the share of pairs in the two industries—one from each industry—that are located less than distance $\overline{d}$ from each other. Larger values of the CDF for a given distance indicate industry pairs that have more compact geographic location patterns with respect to each other.

As for the case of the agglomeration of single industries, we construct confidence bands by drawing random samples of establishments. A key difference is that we restrict the counterfactual to the locations that contain establishments of either industry A or B. Put differently, we take the joint distribution of the establishments in the two industries as our benchmark.

Table 6: Top 10 *most localized* industries (large sample, OKVED 4-digit).

OKVED	Industry name	# of plants	Γ_A
	Western Russia		
2600	Manufacture of other non-metallic mineral products	123	0.738
2214	Publishing of sound recordings	388	0.551
2231	Reproduction of sound recording	122	0.502
2441	Manufacture of basic pharmaceutical products	447	0.453
2215	Other publishing	1,356	0.394
2232	Reproduction of video recording	81	0.386
2741	Manufacture of precious metals	201	0.381
2440	Manufacture of pharmaceuticals	465	0.352
2211	Publishing of books	3,837	0.339
1721	Cotton-type weaving	259	0.328
	Eastern Russia		
2681	Production of abrasive products	41	0.456
2861	Manufacture of cutlery	23	0.420
2741	Manufacture of precious metals	81	0.314
1540	Manufacture of vegetable and animal oils and fats	89	0.261
3410	Manufacture of motor vehicles	164	0.256
3430	Manufacture of parts and accessories for motor vehicles and their engines	230	0.252
2951	Manufacture of machinery for metallurgy	87	0.246
2721	Manufacture of cast iron pipes and cast fitting	18	0.245
2740	Manufacture of non-ferrous metals	39	0.226
2913	Manufacture of pipe line fittings	152	0.221

Notes: Γ_A is computed at 990 kilometers, the last point at which the K-densities are evaluated. We hence measure localization over the whole distance range that we compute the K-densities for using the large samples.

This means that any departure from the counterfactual distribution measures how much closer establishments in the two industries are from each other than from establishments in the two industries in general. This is a strong test since the strength of coagglomeration—i.e., the difference between the observed distribution and the counterfactual distribution—already controls for the agglomeration patterns of the two industries.[11] A direct consequence of this is that some industry pairs can be strongly concentrated geographically, but not be significantly coagglomerated conditional on that geographic concentration (we provide an example below). For each industry pair, we compute global confidence bands based on 1,000 random permutations of the two industries.

3.4 Coagglomeration: Results

Figure 8 depicts four representative examples of coagglomeration patterns. Panel (1) depicts 'Publishing' (OKVED 221) and 'Reproduction of recorded media' (OKVED 223). As shown, those industries are significantly coagglomerated, especially at short distances. They are thus found

[11]Other choices are possible for the counterfactuals. One implication of our specific choice—which provides a stronger test—is that the K-densities of individual industries are not directly comparable to those of industry pairs. The reference distribution—the counterfactual—is different.

Table 7: Top 10 *most geographically concentrated* industries (large sample, OKVED 4-digit).

OKVED	Industry name	# of plants	CDF
	Western Russia		
2600	Manufacture of other non-metallic mineral products	123	0.653
2231	Reproduction of sound recording	122	0.517
2214	Publishing of sound recordings	388	0.509
2441	Manufacture of basic pharmaceutical products	447	0.453
2215	Other publishing	1,356	0.448
2440	Manufacture of pharmaceuticals	465	0.397
2741	Manufacture of precious metals	201	0.388
2211	Publishing of books	3,837	0.374
2232	Reproduction of video recording	81	0.339
2452	Manufacture of perfumes and toilet preparations	520	0.273
	Eastern Russia		
2861	Manufacture of cutlery	23	0.341
2681	Production of abrasive products	41	0.193
2741	Manufacture of precious metals	81	0.182
2734	Manufacture of steel wire	11	0.133
1714	Spinning of flax-type fibres	8	0.126
3511	Building and repairing of ships	506	0.114
2721	Manufacture of cast iron pipes and cast fitting	18	0.111
2463	Manufacture of essential oils	12	0.105
3410	Manufacture of motor vehicles	164	0.099
1540	Manufacture of vegetable and animal oils and fats	89	0.099

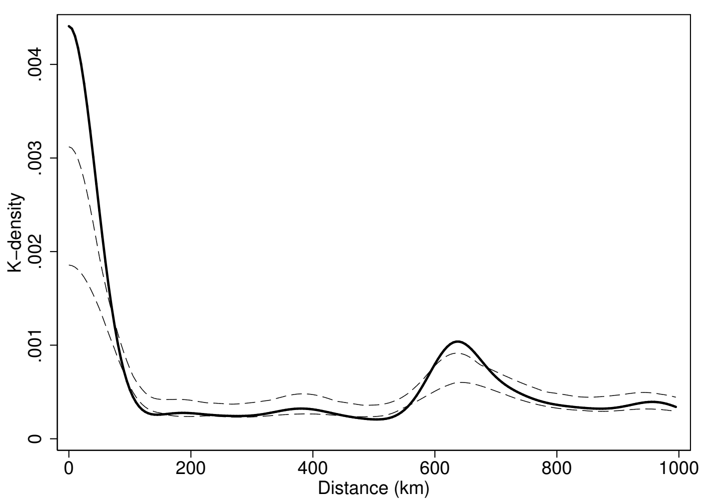
Notes: We report the CDF of the K-density at a distance of $d = 50$km. Hence, the values summarize the share of bilateral distances between pairs of establishments in the industry that is below 50 kilometers.

in the same places, e.g., the same cities. Panel (2) depicts 'Manufacture of other general purpose machinery' (OKVED 292) and 'Manufacture of parts and accessories for motor vehicles and their engines' (OKVED 343). Those two industries are significantly codispersed at short distances, but coagglomerated at longer distances. They thus do not tend to significantly share the same locations but are found in different cities—either nearby cities at about 400 kilometers, or far away ones at about 800–1000km. Panel (a) of Figure 9 shows the corresponding K-density CDF for these two industries. As shown, the two industries are relatively dispersed geographically, which suggests that the coagglomeration at longer distances is essentially due to different regions specializing in these two industries, but with little geographic concentration at short distances. Panel (4) depicts 'Processing and preserving of fish and fish products' (OKVED 152) and 'Manufacture of other wearing apparel and accessories' (OKVED 182). As expected, those industries are codispersed across all distances, meaning that these industries tend to agglomerate into separate clusters.

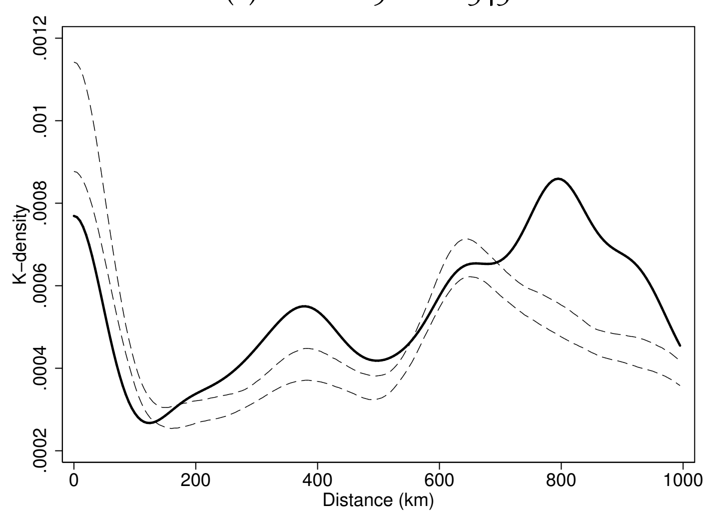
Panel (3) of Figure 8 and panel (b) of Figure 9 are especially interesting. They depict the coagglomeration K-density and CDF of 'Spinning of textile fibres' (OKVED 171) and 'Weaving manufacture' (OKVED 172), respectively. Figure 2 illustrates the location patterns of these two industries in the Moscow region. As shown, they are both strongly concentrated geographically, and they are also close to each other. However, as shown in Figure 8, these two industries are not significantly coagglomerated *conditional on the overall concentration of those two industries*. Indeed, the observed K-density falls into the 90% confidence band. Yet, as can be seen from panel (b) of Figure 9, the coagglomeration CDF of the industry pair 171–172 is significantly larger than the average or the median CDF across industry pairs, consistent with panel (b) of Figure 2. In other words, the industry pair 171–172 is strongly concentrated geographically because both industries are strongly concentrated and tend to locate in the same areas. However, conditional on this, the two industries are *not closer to each other than predicted by a random allocation of that industry*. This finding suggests that these industries may be attracted by unobserved local factors such as an adequate labor force or infrastructure. It also highlights that the test on coagglomeration is a fairly stringent one since it controls for the geographic concentration of the individual industries of the industry pair we consider.

Figure 8: K-density estimations for selected OKVED 3-digit industries (all of Russia, medium sample).

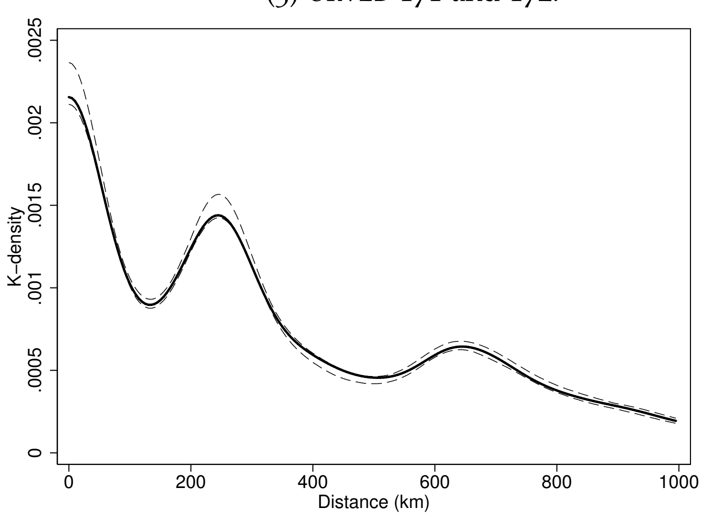
(1) OKVED 221 and 223.



(2) OKVED 292 and 343.



(3) OKVED 171 and 172.



(4) OKVED 152 and182.

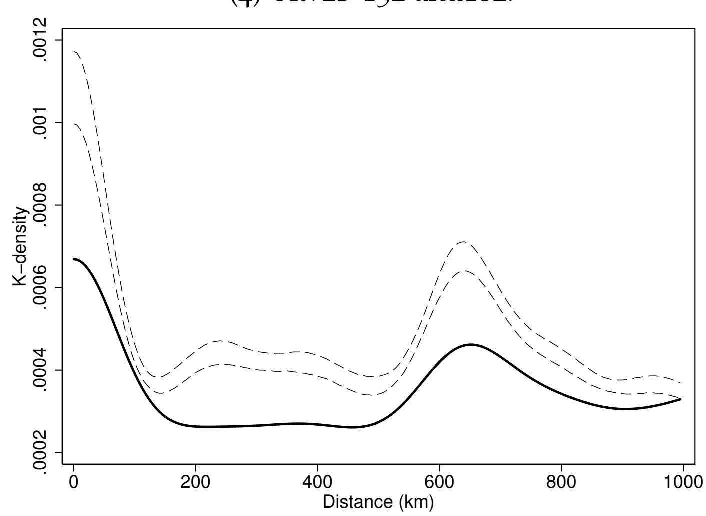


Table 8 summarizes the numbers of significantly coagglomerated, codispersed, and random industry pairs for all of Russia. As can be seen from that table, a large share of industry pairs (more than 70%) are significantly coagglomerated. In other words, there is substantial cross-industry structure in the Russian agglomeration patterns, more than for example in Canada (see Behrens, 2016; and Behrens and Guillain, 2017). This information is useful and likely to reflect the benefits that industries derive from being close to each other.[12] We return more formally to this point in Section 4.

Figure 9: K-density CDF for selected OKVED 3-digit industries (all of Russia, medium sample).

(a) OKVED 292 and 343. (b) OKVED 171 and 172.

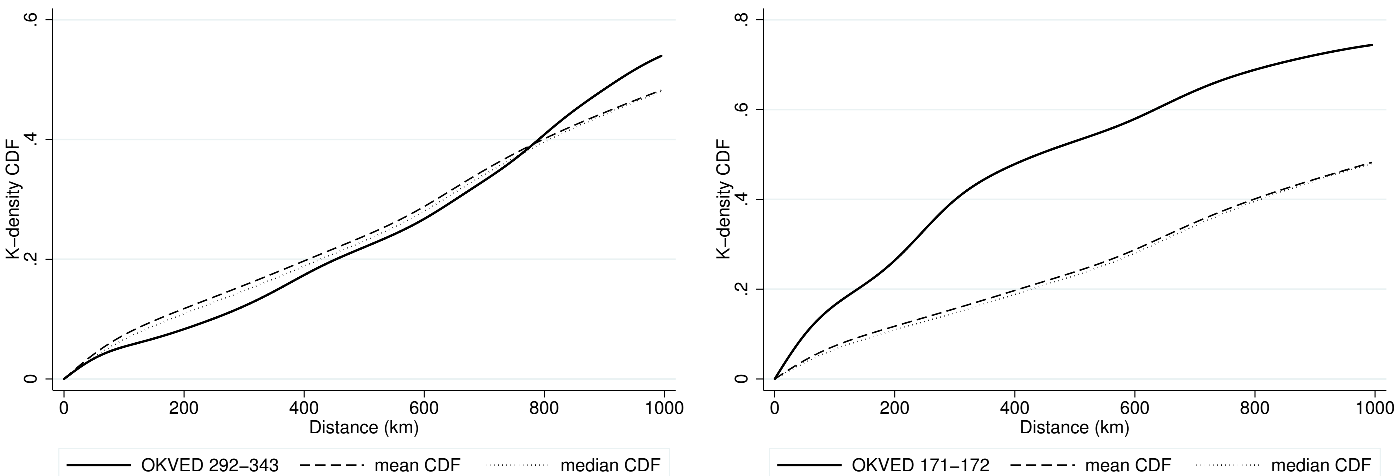


Figure 10 shows the number of significantly coagglomerated industry pairs (panel (a)) and the number of significantly codispersed industry pairs (panel (b)) by distance. As can be seen from that figure, there is substantial coagglomeration at short distances and even more at around 650–700 kilometers, which corresponds to the distance between Moscow and Saint Petersburg. This suggests that some industry pairs tend to cluster at short distances within major metro areas, whereas others tend to cluster separately in different metro areas. Table 9 shows that the industry pairs that are significantly coagglomerated at short distances are generally different than those that are significantly coagglomerated at intermediate distances. In a nutshell, some industries tend to be close together, whereas the industrial tissue of Moscow and Saint Petersburg (the second spike in panel (a) of Figure 10) differs. There are relatively few industry pairs that are coagglomerated both at short and at long distances.

Turning to the strength of the coagglomeration and codispersion patterns, Figure 11 shows that the two are highly skewed but roughly equal in terms of magnitude and distribution. Hence, both for coagglomeration and codispersion there are only a few highly coagglomerated

[12] Helsley and Strange (2014) show that coagglomeration patterns do not necessarily need to reflect beneficial agglomeration forces. However, numerical experiments performed by O'Sullivan and Strange (2017) suggest that this is, on average, the case.

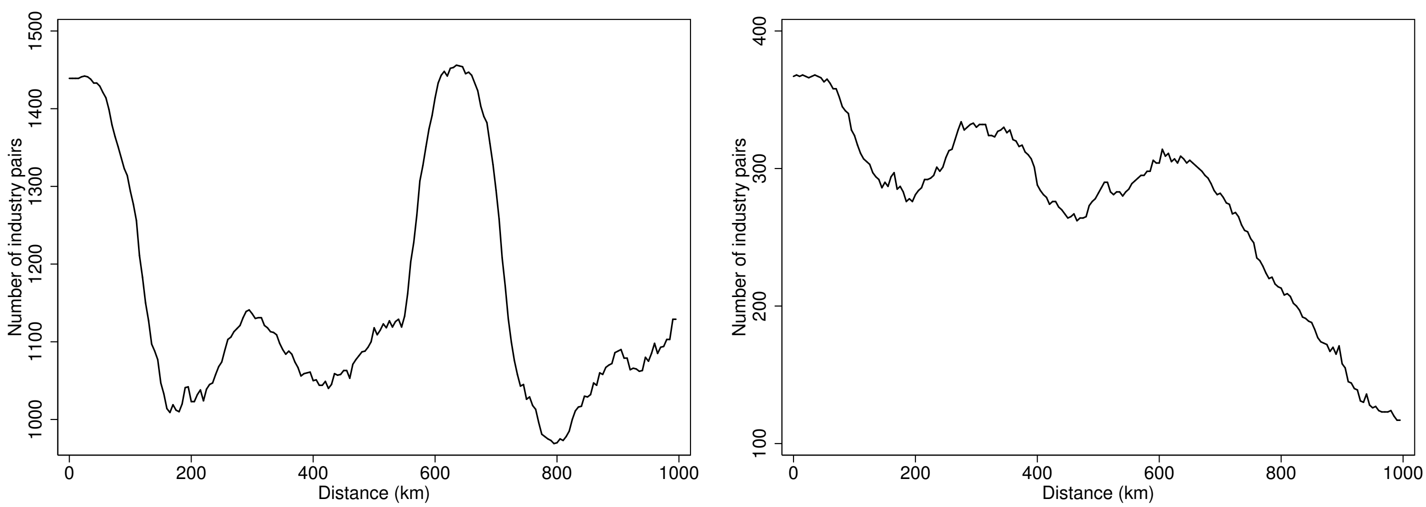
Table 8: Summary statistics for K-density estimates for coagglomeration patterns.

Coagglomeration status	Number of industry pairs	Percentages
Coagglomerated	3,771	72%
Random	771	15%
Codispersed	711	13%
Total	5,253	100%
$\overline{\Gamma}\vert_{\Gamma_i>0}$	0.011	
$\overline{\Psi}\vert_{\Psi_i>0}$	0.010	

Notes: All K-densities are computed for a range of 0–1000 kilometers for 5,253 3-digit industry pairs. The values of $\overline{\Gamma}|_{\Gamma_i>0}$ and $\overline{\Psi}|_{\Psi_i>0}$ are computed at the last point at which the K-densities are evaluated, i.e., 995km. We report average values for all significantly localized industry pairs in the case of $\overline{\Gamma}|_{\Gamma_i>0}$, and for all significantly dispersed industry pairs in the case of $\overline{\Psi}|_{\Psi_i>0}$.

Figure 10: Coagglomeration and codispersion by distance (all of Russia, medium sample).

(a) Coagglomeration. (b) Codispersion.



or codispersed industry pairs. For most industry pairs, the strength of coagglomeration or codispersion is not very large. Note however that this result needs to be interpreted with caution. Indeed, as shown before, the strength of coagglomeration is measured *conditional on the geographic concentration of the two industries*. Controlling for that own-industry concentration can make two very strongly concentrated industries appear to be only weakly coagglomerated (or not at all; see panel (3) of Figure 8).

Finally, Table 10 summarizes the coagglomeration patterns by broad 2-digit industries. Panel (a) reports the coagglomeration of 3-digit industries (broken down by their 2-digit industry) with other 3-digit industries that do not belong to the same 2-digit industry. Panel (b) reports the coagglomeration of the 3-digit industries within the 2-digit industry with other industries that do belong to the same 2-digit industry. As can be seen, some industries display

Figure 11: Skewness of the strength of coagglomeration/codispersion, (all of Russia, medium sample).

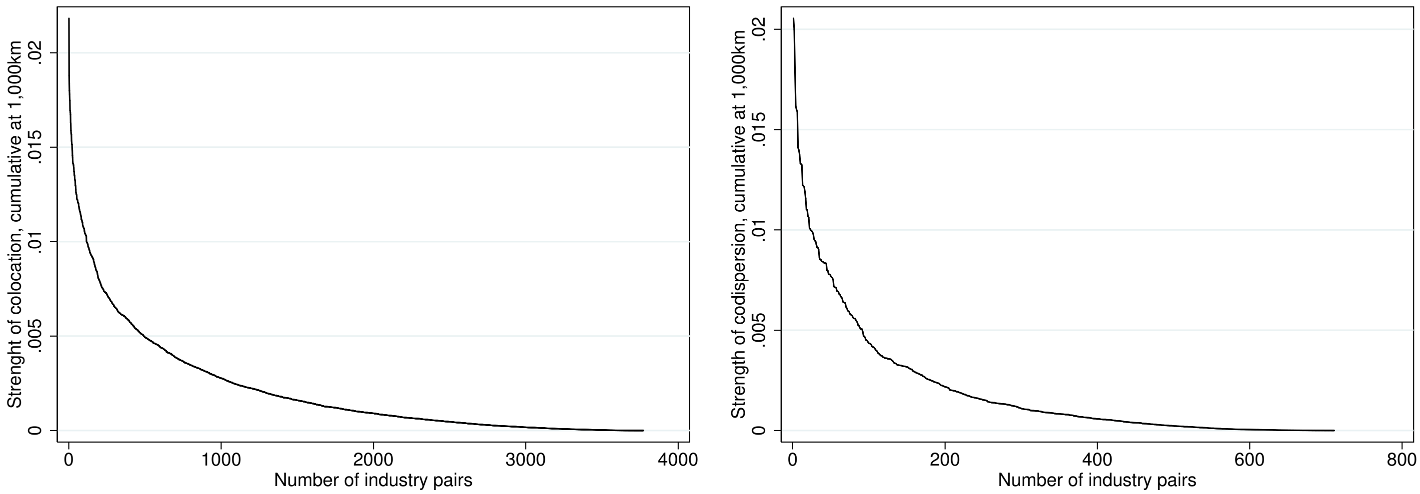


Table 9: Coagglomerated industries at short and at intermediate distances

Type of coagglomeration	# of pairs
Coagglomerated on 0–170km, but not on 550–750km	1,421
Coagglomerated on 550–750km, but not on 0–170km	654
Coagglomerated on 0–170km and on 550–750km	479

Notes: Breakdown of all coagglomerated industry pairs on 0–170km and on 550–750km.

strong coagglomeration patterns within the same 2-digit industry (e.g., 'Publishing, printing and reproduction of recorded media'), whereas other industries are relatively codispersed (e.g., 'Manufacture of coke, refined petroleum products and nuclear fuel'). As can be further seen, some industries also display strong coagglomeration patterns with most other industries that are not in the same 2-digit industry. This might indicate industries that are very 'urban', and which appear to be coagglomerated with most other 'urban' industries. Note, finally, that the overall share of significantly coagglomerated industry pairs is roughly similar within and between 2-digit industries, around 70%. Hence, coagglomeration patterns are pervasive and cut across most industrial boundaries.

4 The determinants of agglomeration and coagglomeration of Russian manufacturing industries

Until now, we have documented that there are many localized and geographically concentrated industries in Russia. For some of those industries, especially in the west, the extent of geographic concentration is large. What are the potential drivers of this agglomeration and co-

Table 10: Coagglomeration patterns by broad industry groups.

OKVED2 ind.	Industry name	number of 3-digit industries in the 2-digit sector that are coagglomeration with ...							
		(a) outside same 2-digit				(b) within same 2-digit			
		local.	disp.	rand.	% local.	local.	disp.	rand.	% local.
15	Manufacture of food products and beverages	652	132	62	77.07	25	7	4	69.44
16	Manufacture of tobacco products	21	11	70	20.59				
17	Textile manufacture	603	42	27	89.73	13	2	6	61.90
18	Manufacture of wearing apparel; dressing and dyeing of fur	193	60	47	64.33	1	2	0	33.33
19	Manufacturing of leather; leather articles and manufacture of footwear	227	32	41	75.67	2	1	0	66.67
20	Woodworking and manufacture of wood and cork articles, except furniture	377	61	52	76.94	9	1	0	90.00
21	Manufacture of cellulose, pulp, paper, cardboard and articles of these materials	128	30	44	63.37	0	0	1	0.00
22	Publishing, printing and reproduction of recorded media	268	20	12	89.33	3	0	0	100.00
23	Manufacture of coke, refined petroleum products and nuclear fuel	79	93	128	26.33	0	1	2	0.00
24	Manufacture of chemicals and chemical products	467	77	128	69.49	13	1	7	61.90
25	Manufacture of rubber and plastic products	148	27	27	73.27	0	1	0	0.00
26	Manufacture of other non-metallic mineral products	508	143	109	66.84	18	6	4	64.29
27	Manufacture of basic metals	323	67	100	65.92	7	0	3	70.00
28	Manufacture of fabricated metal products	470	147	55	69.94	10	10	1	47.62
29	Manufacture of machinery and equipment	469	85	118	69.79	16	0	5	76.19
30	Manufacture of office machinery and computers	98	2	2	96.08				
31	Manufacture of electrical machinery and apparatus	434	69	79	74.57	13	2	0	86.67
32	Manufacture of radio, television and communication electronic components and apparatus	245	31	24	81.67	3	0	0	100.00
33	Manufacture of medical instruments, measure, control and test devices, optical devices, photo and cine equipment, watches	356	74	60	72.65	8	1	1	80.00
34	Manufacture of motor vehicles, trailers and semi-trailers	223	45	32	74.33	2	1	0	66.67
35	Manufacture of ships, aircaft and spacecraft and other transport	307	35	148	62.65	6	1	3	60.00
36	Manufacture of furniture	463	40	79	79.55	14	0	1	93.33
37	Recycling of secondary raw materials	155	25	22	76.73	1	0	0	100.00
Total		7,214	1,348	1,466	—	164	37	38	—

Notes: There is a total of 10,506 (non-unique) industry pairs. The total in column (a) includes the reciprocal pairs ij and ji; since we allocate the pair ij to the 2-digit sector of i and the pair ji to the 2-digit sector of j, they do not enter the computations symetrically. The industry pairs ij within the same 2-digit sector are counted in column (b). In that case, we exclude the reciprocal pairs ji (239 in total) as they enter the computations symmetrically. Hence, the total number of reported pairs is 10,028 (column (a)) plus 239 (column (b)), excluding the 239 reciprocal pairs in column (b).

agglomeration of industries? Is it buyer-supplier links between industries? Low transportation costs? Common labor pools? Knowledge sharing? Or any combination of these 'Marshallian' agglomeration forces? To provide a first set of answers to these questions, we now regress our measures of geographic concentration—both for individual industries and for industry pairs—on various proxies that are theoretically associated with the agglomeration of industries.

There is a long literature in this tradition.[13] Following that literature, we consider the following proxies for the Marshallian agglomeration forces: (i) input-output coefficients between industries to capture buyer-supplier relationships; (ii) the similarity of the workforce hired by the industries to capture thick local labor markets; and (iii) the intensity with which patents originating in an industry—or being used by an industry—come from the other industries. We add to these forces another one that has been considered only little until now in the literature: (iv) the ad valorem transport costs for shipping the industries' output.

Ideally, we would like to use Russian industry-level data. Unfortunately, we do not have them, and there is little hope of getting them. This lack of data—and more generally the absence of work on the geographic concentration of industries in Russia—is one of the key reasons that explains why the drivers of geographic concentration have, to our knowledge, never been directly investigated for Russia until now.[14] To deal with this problem, we will replace the missing Russian data with high-quality data from Canada and the U.S. For these countries, we have good measures of input-output links, labor force similarity, patent citations, and ad valorem transport costs. We make use of the OKVED 3-digit classification and construct a crosswalk with the NAICS 4-digit classification. We retain only industries for which the correspondence is clear. Details concerning the crosswalk, as well as our data on input-output links, labor market pooling, knowledge exchange, and transport costs are provided in Appendix B. The idea of using Canadian and U.S. data to proxy for the Russian data is that the relationships we are interested in are mainly technological. Hence, they should also operate in Russia. As a by-product of this approach, note that our right-hand side variables are reasonably exogenous. Indeed, it is unlikely that the geographic concentration of industries in Russia is a driver of the Canadian input-output tables or trucking ad valorem transport costs, thus removing all problems of reverse causality. The strategy that we use is similar to that in Ellison et al. (2010)

[13]See, among others, Rosenthal and Strange (2001); Ellison et al. (2010); Faggio et al. (2017); Behrens, Bougna, and Brown (2018); and Behrens and Brown (2018). Combes and Gobillon (2015) provide a critical discussion of this approach and of its potential limitations.

[14]Quality data on input-output links, similarity of the labor force across industries, or patent citations are either in short supply or simply non-existent for Russia. Concerning the labor force composition of the different industries, this information is available only for 'letters/characters', i.e., the most aggregated level of OKVED (see `http://www.gks.ru/bgd/regl/b15_11/IssWWW.exe/Stg/d01/06-04.htm`). There are some basic input-output tables which could be used and which are aggregated between the 2- and 3-digit level (`http://www.gks.ru/wps/wcm/connect/rosstat_main/rosstat/ru/statistics/accounts/`). However, it seems that no information after 2011 is available. Last, concerning patent data, there are only the total number of patents across regions. There is no information about patent citations across industries.

who instrument U.S. industry-level characteristics using their U.K. counterparts.

We start with the determinants of the geographic concentration of individual industries. As argued by Ellison et al. (2010) and Combes and Gobillon (2015), this approach is unlikely to yield strong results since there are only a small number of observations and since it is hard to have good proxies for input-output links, labor market pooling, and knowledge exchange. These variables operate mostly across *different* industries, and they are hard to measure at the level of individual industries. However, we have good measures of industry-level ad valorem transport costs, and we will use these to investigate whether high transport cost industries are more or less geographically concentrated in Russia.

Table 11: Transport costs and geographic concentration in Russia.

Variables	(1) (All Russia)	(2) (All Russia)	(3) (West)	(4) (West)	(5) (East)	(6) (East)
	(a) Dep. variable: K-density CDF					
AV transport costs	-0.386^b	-0.439^c	-0.394^b	-0.457^c	-0.121	-0.185
	(0.159)	(0.231)	(0.165)	(0.233)	(0.137)	(0.154)
Industries	All	Exact	All	Exact	All	Exact
Observations	77	45	77	45	77	45
R^2	0.069	0.081	0.070	0.086	0.007	0.020
	(b) Dep. variable: Excess agglomeration Γ_A					
AV transport costs	-0.335^b	-0.437^c	-0.342^c	-0.472^c	-0.204	-0.230
	(0.166)	(0.247)	(0.175)	(0.254)	(0.144)	(0.149)
Industries	All	Exact	All	Exact	All	Exact
Observations	77	45	77	45	77	45
R^2	0.050	0.074	0.051	0.082	0.018	0.026

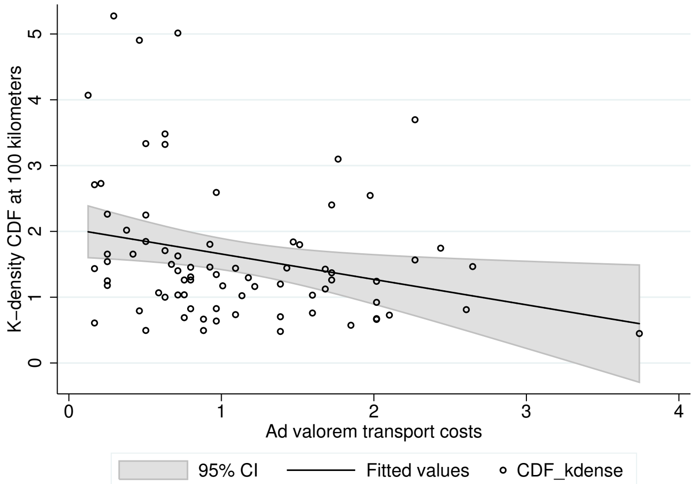
Notes: Coefficients significant at: ^{a} 1%; ^{b} 5%; and ^{c} 10%. Robust standard errors in parentheses. The dependent variables is the DO K-density CDF at 100 kilometers distance. All variables are standardized. 'All' industries includes all 100 industries for which we have a crosswalk (either exact or approximative) from OKVED 3-digit to NAICS 4-digit. 'Exact' industries includes only the 45 industries for which we have an exact crosswalk.

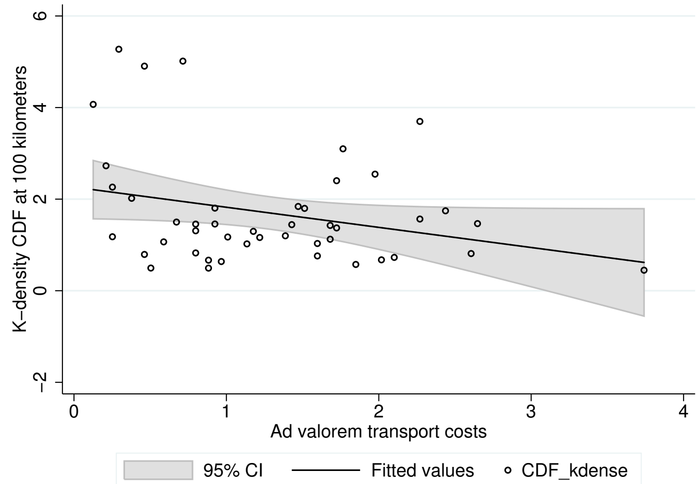
Table 11 summarizes the results of simple regressions of industry-level geographic concentration on ad valorem transport costs. As shown: (i) all coefficients are negative, in accord with Krugman's (1991) model of economic geography—lower transport costs are associated with more geographic concentration; and (ii) lower transport costs are associated with more specialization. This latter result can be seen from panel (b), where we use our measure of excess agglomeration as the dependent variables. Note that the coefficient on transport costs is consistently negative. It is significant for the west and for all of Russia, but it is not significant for the east. The latter is due to larger standard errors due to smaller sample sizes when computing the K-densities. Overall, the result is robust and in line with findings for Canada as documented by Behrens et al. (2018) and Behrens and Brown (2018). Figure 12 below illustrates the relationship—for all of Russia at 100 kilometers distance—using only industries for which we have an 'exact' industry crosswalk.

Figure 12: Geographic concentration patterns and ad valorem transport costs.

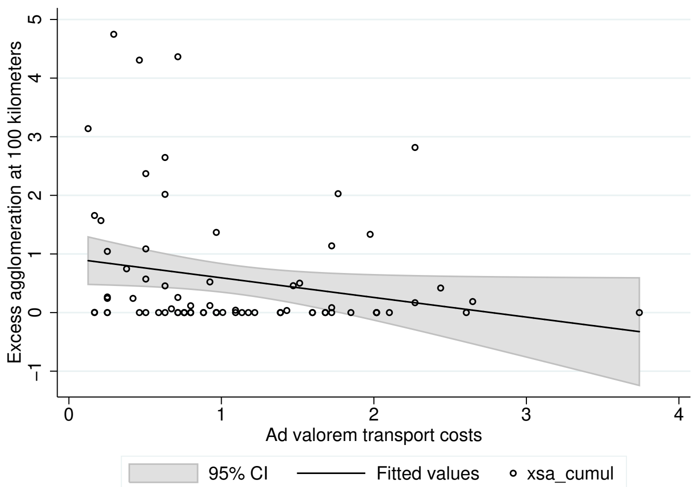
(a) All industries. (b) Exact matches.

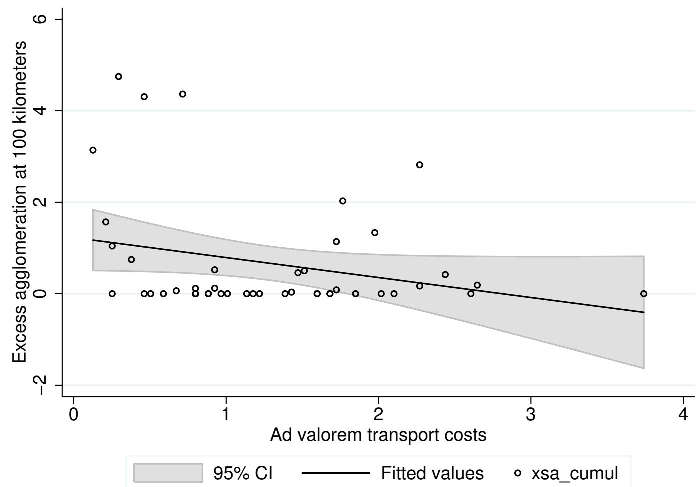
(1) K-density CDF.





(2) Excess agglomeration.





While the foregoing exercise is useful to show that transport costs could be a key driver of geographic concentration in Russia, it does not allow to take into account the other Marshallian agglomeration forces. To capture those, we now repeat the foregoing exercise using as the dependent variable the CDF of our coagglomeration K-densities and controlling for input-output links, workforce similarity, and patent citations (see Behrens and Brown, 2018).[15]

Our key results are summarized in Tables 12 and 13. Table 12—especially regressions (8),

[15]We do not run regressions using the excess coagglomeration as dependent variable. Contrary to the geographic concentration of one industry—where the benchmark is the overall distribution of manufacturing—the benchmark for the coagglomeration measures is the joint distribution of both industries. The measure of excess concentration is thus more difficult to use in regressions since it only measures the concentration of the industries above their own concentration. Hence, in what follows, we disregard that measure.

(9), and (10)—shows that: (i) industries with stronger input-output links are more coagglomerated; (ii) industries that exchange more knowledge are more coagglomerated; (iii) industries with higher transport costs tend to be less coagglomerated. These results are robust and in line with what has been found for other countries like Canada and the U.S. However, as can also be seen, (iv) industries that hire more similar workers tend to be less coagglomerated in Russia. This result differs from what has been found previously in the literature. One possible explanation lies in the low mobility of workers between firms and regions (see, e.g., Guriev and Vakulenko (2015) for evidence on 'geographic poverty traps' in Russia). Especially low-skilled workers—the bulk of the workforce in Russian manufacturing—are not mobile: low salaries, combined with a substantial demand for cheap labor in manufacturing, does not stimulate labor mobility or investment in human capital.[16] Another peculiarity of Russian institutions lies in the mismatch between the education system and the demand for manual professions. Employers solve this problem by providing firm-specific training right in the workplace. Since workers are contractually bound to firms in return for training—and since the training is firm specific and therefore not easily portable—this impedes the mobility between firms and reduces the need to be close to other employers requiring similar labor types.

Regressions (15)–(19) in Table 13 follow Behrens and Brown (2018) and interact the input-output coefficients with industries' transport costs. The idea is that high transport costs should be more important drivers of coagglomeration if industries buy and sell a lot from each other. Our results show that industries that buy a lot from each other—as measured by their input-output coefficients—tend indeed to be more coagglomerated if transporting their output is relatively expensive. Although this result is not super robust across the different specifications, it nevertheless seems to be borne out in the data. Hence, the econometric analysis of coagglomeration patterns again suggests that transport costs may play a key role for geographic concentration in Russia.

5 Conclusions

We have painted a detailed picture of geographic concentration patterns of manufacturing industries in Russia using disaggregated microgeographic data. We have also investigated the determinants of these patterns, both for the agglomeration of individual industries and the coagglomeration of industry pairs. Our results show that the geographic patterns of Russian

[16]For example, the average wage across all sectors in Russia was 34,029.5 rub in 2015. In manufacturing, the average was 31,910.2 rub, while in textile manufacturing it was only 15,757.6 rub. See http://www.gks.ru/wps/wcm/connect/rosstat_main/rosstat/ru/statistics/wages/labour_costs/# for more information. One explanation for the low manufacturing wages may be the weak bargaining power of trade unions (see, e.g., Lukiyanova and Vishnevskaya, 2016). Another may be simply the weak manufacturing productivity itself, which should translate into low wages.

Table 12: The determinants of manufacturing coagglomeration in Russia.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12) (Exclude 3)	(13) (Exclude 3)	(14) (Exclude 3)
IO-coefficients (max)	0.032^c							0.058^a	0.046^b	0.064^a		0.057^a	0.042^b	0.061^a
	(0.018)							(0.020)	(0.019)	(0.020)		(0.021)	(0.021)	(0.021)
IO-coefficients (average)		0.026									0.059^a			
		(0.019)									(0.019)			
AV transport costs (average)			-0.224^a					-0.217^a		-0.221^a	-0.218^a	-0.203^a		-0.209^a
			(0.020)					(0.020)		(0.020)	(0.020)	(0.020)		(0.020)
AV transport costs (max)				-0.172^a					-0.165^a				-0.151^a	
				(0.020)					(0.020)				(0.020)	
Occupational similarity					-0.042^b			-0.105^a	-0.112^a	-0.097^a	-0.107^a	-0.108^a	-0.114^a	-0.095^a
					(0.018)			(0.019)	(0.020)	(0.019)	(0.020)	(0.021)	(0.021)	(0.020)
Patent citations (use)						0.094^a		0.072^a	0.091^a		0.074^a	0.090^a	0.109^a	
						(0.022)		(0.023)	(0.023)		(0.023)	(0.029)	(0.029)	
Patent citations (make)							0.083^a			0.061^a				0.051^b
							(0.022)			(0.022)				(0.022)
Observations	2,535	2,535	2,535	2,535	2,535	2,535	2,535	2,535	2,535	2,535	2,535	2,403	2,403	2,403
R-squared	0.001	0.001	0.050	0.030	0.002	0.009	0.007	0.062	0.043	0.061	0.062	0.056	0.038	0.054

Notes: Coefficients significant at: ^{a} 1%; ^{b} 5%; and ^{c} 10%. Robust standard errors in parentheses. The dependent variables is the DO coagglomeration K-density at 100 kilometers distance. All variables are standardized. See Appendix B for a detailed description of our data. We only include industry pairs for which we have an exact crosswalk from OKVED 3-digit to NAICS 4-digit for both industries in the pair. 'Exclude 3' regressions exclude all NAICS 4-digit industry pairs within the same NAICS 3-digit industries.

Table 13: The determinants of manufacturing coagglomeration in Russia, with interactions.

	(15)	(16)	(17) (Exclude 3)	(18) (Exclude 3)	(19) (Exclude 3)
IO-coefficients (max)	0.048	0.036	-0.061	-0.058	
	(0.050)	(0.047)	(0.071)	(0.061)	
IO-coefficients (average)					-0.078
					(0.065)
AV transport costs (average)		-0.222^{a}		-0.216^{a}	-0.218^{a}
		(0.021)		(0.022)	(0.022)
AV transport costs (max)	-0.165^{a}		-0.161^{a}		
	(0.021)		(0.022)		
Occupational similarity	-0.112^{a}	-0.104^{a}	-0.109^{a}	-0.102^{a}	-0.101^{a}
	(0.020)	(0.019)	(0.021)	(0.021)	(0.021)
Patent citations (use)	0.091^{a}	0.074^{a}	0.108^{a}	0.087^{a}	0.087^{a}
	(0.024)	(0.023)	(0.030)	(0.029)	(0.029)
IO-coefficients (max) $\times$ AV transport costs (max)	-0.002		0.105		
	(0.043)		(0.064)		
IO-coefficients (max) $\times$ AV transport costs (average)		0.026		0.123^{b}	
		(0.039)		(0.053)	
IO-coefficients (average) $\times$ AV transport costs (average)					0.160^{a}
					(0.062)
Industries	Exact	Exact	Exact	Exact	Exact
Observations	2,535	2,535	2,403	2,403	2,403
R-squared	0.043	0.062	0.039	0.057	0.057

Notes: Coefficients significant at: ^{a} 1%; ^{b} 5%; and ^{c} 10%. Robust standard errors in parentheses. The dependent variables is the DO coagglomeration K-density at 100 kilometers distance. All variables are standardized. See Appendix B for a detailed description of our data. We only include industry pairs for which we have an exact crosswalk from OKVED 3-digit to NAICS 4-digit for both industries in the pair. 'Exclude 3' regressions exclude all NAICS 4-digit industry pairs within the same NAICS 3-digit industries.

manufacturing are broadly comparable—both in extent and strength—to those that have been documented for other countries. Furthermore, most drivers of agglomeration seem similar: stronger buyer-supplier links, more knowledge exchange, and lower transport costs yield more geographically concentrated patterns for manufacturing industry pairs. The only substantive difference that we find, compared to other countries, is that industries with a more similar workforce appear to be less coagglomerated.

This latter point may be explained by specificities of the Russian labor market—like the prevalence of firm-specific non-portable training of workers—which makes the bulk of the manufacturing workforce relatively immobile between regions and firms. This may be problematic for several reasons. First, it is known that whether human capital investments lead to more or less geographic concentration depends on whether they are industry- or firm-specific (see Matouschek and Robert-Nicoud, 2005). The presence of monopsony power on the employer side—due to less coagglomeration of industries that require similar workers—reduces wages and stifles workers' investment decisions to acquire general human capital. Second, the positive benefits of insurance against idiosyncratic shocks are lost. Last, knowledge exchange and innovation due to the rapid mobility of workers across jobs and firms ('job hopping'; see, e.g., Fallick, Fleischman, and Rebitzer, 2006) are also foregone. Our findings suggest that understanding the role that labor market arrangements play in the geographic concentration process in Russia is key to understanding more globally the drivers and potential consequences of that concentration. Labor markets are the first policy lever uncovered by our analysis.

The second policy lever resides in transportation costs, which seem to play a key role for geographic concentration and regional specialization patterns. We consistently find that industries that face higher transport costs—measured using industry-level ad valorem trucking costs—are more geographically dispersed than industries that face lower transport costs. Although Russia does have a 'transport strategy' until 2030—which was published in 2008—there have been only minor revisions or alterations to that strategy in 2014. A quickly degrading and partially overloaded infrastructure in the west, almost non-existent infrastructure in the east, and the domination of monopolies for air- and rail-transportation all add up to an environment where transport costs may be high enough to slow down or impede the process of geographic concentration. The less concentrated geographic distribution—though positive from a regional cohesion perspective—may come at the cost of foregone productivity.

One last word of caution is in order. As mentioned before, the geographic concentration patterns in the 1990s were largely a legacy of the Soviet planned economy. Put differently, these patterns were not determined by market forces (Kofanov et al., 2015). Since spatial patterns are relatively persistent, the patterns we pick up in 2012–2014 may still be to some (large) extent a legacy of the past. Should that be the case, the foregoing policy conclusions should be considered cautiously as the location patterns may not be the result of market forces. However, what would be remarkable in that case is that they still obey rules that seem similar to those that prevail in a market economy.

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Data appendix

This appendix contains detailed information on the way that we collected and processed our data, as well as on the different data sources.

A. Plant-level data.

A.1. Overview, sources, and data cleaning. Our main dataset is the RUSLANA database from Bureau Van Dijk Electronic Publishing (BvDEP; see `http://www.ruslana.bvdep.com`). This database contains information about Russian companies, most notably contact information (addresses) and activity codes. The database provides legal, operational, postal, and *de facto* address information. We use the *de facto* addresses, which come from open sources (call-center Credinform, business catalogues, electronic trading platforms, companies' websites etc). According to BvDEP there are a large number of yearly updates of these contact details. Identification of companies and establishments in our data is based on the Taxpayer's Identification Number (INN) and the All-Russian Classifier of Enterprises and Organizations (OKPO) pair.

We only look at the manufacturing portion of the RUSLANA database. From official statistics ('Monthly report of the socioeconomic situation in Russia', Russian Bureau of Statistic, January 2014 and 2015), there were 405,000 registered manufacturing companies (8.2% of all companies in Russia) in 2013, and 403,100 registered manufacturing companies (8.3% of all companies in Russia) in 2014. The raw version of the 2014 RUSLANA database contains 774,469 manufacturing establishments. Primary data cleaning—removing establishments with no address information and those in the Republic of Crimea—reduce our sample to 726,897 establishments. We then discard plants based on their activity status. The raw version of the database contains many establishments that have been liquidated, are in the process of being liquidated, or have otherwise been removed from the state register. We drop all those establishments. We further keep only those establishments whose contact information were updated between 2012 and 2014. These operations yield a database of 345,384 establishments with address information in 2012–2014. Of these, we can precisely geocode 320,934 companies (see Appendix A.2 below). We believe that the 2014 address information is the most precise, whereas the 2012–2013 information may be less up-to-date. Limiting ourselves to companies with address information in 2014, we have a total number of 178,138 establishments. We refer to this sample as the *'small sample'*. Adding the establishments with 2013 address information yields the *medium sample* (256,943 establishments); and adding the establishments with 2012 address information yields the *large sample* (319,684 establishments). The large and medium samples may be a bit noisier since they may contain establishments that are no longer located at the indicated address. However, the large sample is much more exhaustive. If plants do not move frequently—which is usually the case—then using the large sample should provide a more accurate picture of the

Table 14: Count of plants for the large sample, by 3-digit OKVED and east-west location.

OKVED	Industry name	# plants west	# plants east
151	Production, processing and preserving of meat and meat products	4,849	1,727
152	Processing and preserving of fish and fish products	1,633	916
153	Processing and preserving of potato, fruit and vegetables	1,377	385
154	Manufacture of vegetable and animal oils and fats	830	227
155	Manufacture of dairy products	2,562	851
156	Manufacture of grain mill products, starches and starch products	1,639	597
157	Manufacture of prepared animal feeds	873	268
158	Manufacture of other food products	10,088	3,614
159	Manufacture of beverages	3,510	1,132
160	Manufacture of tobacco products	98	14
171	Spinning of textile fibres	453	42
172	Weaving manufacture	658	41
173	Finishing of textiles	373	53
174	Manufacture of made-up textile articles, except apparel	2,721	625
175	Manufacture of other textiles	1,328	230
176	Manufacture of textile fabrics	106	13
177	Manufacture of knitted goods	1,123	195
181	Manufacture of leather clothes	479	106
182	Manufacture of other wearing apparel and accessories	9,734	2,061
183	Dressing and dyeing of fur; manufacture of articles of fur	392	85
191	Tanning and dressing of leather	128	14
192	Manufacture of luggage, handbags and the like, saddlery and harness	528	59
193	Manufacture of footwear	1,062	200
201	Sawmilling and planing of wood, impregnation of wood	8,949	3,858
202	Manufacture of veneer, plywood, cauls, panels	624	203
203	Manufacture of wooden building constructions, including wooden pre-engineered buildings and millwork	6,251	1,854
204	Manufacture of wooden containers	804	160
205	Manufacture of other products of wood; manufacture of articles of cork, straw and plaiting materials	1,312	391
211	Manufacture of cellulose, pulp, paper and cardboard	602	99
212	Manufacture of articles of paper and paperboard	2,641	524
221	Publishing	19,142	4,593
222	Printing and service activities related to printing	12,211	2,983
223	Reproduction of recorded media	438	49
231	Manufacture of coke oven products	17	13
232	Manufacture of refined petroleum products	1,330	282
233	Processing of nuclear fuel	34	7
241	Manufacture of basic chemicals	3,028	700
242	Manufacture of pesticides and other agro-chemical products	137	34
243	Manufacture of paints and varnishes	1,193	324
244	Manufacture of pharmaceuticals	1,943	316
245	Manufacture of soap, cleaning and polishing preparations, perfumes and toilet preparations	1,453	265
246	Manufacture of other chemical products	1,300	280
247	Manufacture of artificial and synthetic fibres	119	22
251	Manufacture of rubber products	1,307	420
252	Manufacture of plastic products	11,155	3,059
261	Manufacture of glass and glass products	2,196	483
262	Manufacture of ceramic goods not used in construction	758	208
263	Manufacture of ceramic tiles and flags	376	118
264	Manufacture of bricks, tiles and construction products, in baked clay	1,259	414
265	Manufacture of cement, lime and plaster	433	153
266	Manufacture of articles of concrete, plaster or cement	9,162	3,218
267	Cutting, shaping and finishing of decorative and building stone	1,582	495
268	Manufacture of other non-metallic mineral products	1,557	676
271	Manufacture of crude iron, ferroalloy, steel	694	314
272	Manufacture of crude iron and steel pipes	265	97
273	Cast iron and steel other primary processing	616	208
274	Manufacture of non-ferrous metals	694	269
275	Casting of metals	552	202

Table 14 (continued).

281	Manufacture of constructional metal products	12,070	3,963
282	Manufacture of metal tanks, reservoirs and containers; manufacture of central heating radiators and boilers	1,036	455
283	Manufacture of steam generators, except central heating hoboilers; manufacture of nuclear reactors	438	229
284	Forging, pressing, stamping and roll forming of metal; powder metallurgy	1,119	348
285	Treatment and coating of metals; general mechanical engineering	5,275	1,764
286	Manufacture of cutlery, tools and general hardware	781	204
287	Manufacture of other fabricated metal products	4,449	1,276
291	Manufacture of machinery	3,938	1,082
292	Manufacture of other general purpose machinery	13,936	4,324
293	Manufacture of agricultural and forestry machinery	1,224	385
294	Manufacture of machine-tools	1,919	479
295	Manufacture of other special purpose machinery	3,842	1,270
296	Manufacture of weapons and ammunition	268	53
297	Manufacture of domestic appliances	399	124
300	Manufacture of office machinery and computers	2,220	385
311	Manufacture of electric motors, generators and transformers	1,769	656
312	Manufacture of electricity distribution and control apparatus	3,273	929
313	Manufacture of insulated wire and cable	465	80
314	Manufacture of accumulators, primary cells and primary batteries	127	26
315	Manufacture of lighting equipment and electric lamps	858	189
316	Manufacture of other electrical equipment	3,518	1,056
321	Manufacture of electronic and radio components, electrovacuum devices	890	114
322	Manufacture of television and radio transmitters and apparatus for electric communications	1,214	292
323	Manufacture of television and radio receivers, sound or video recording or reproducing apparatus and associated goods	1,486	387
331	Manufacture of medical and surgical equipment and orthopaedic appliances	2,764	612
332	Manufacture of instruments and appliances for measuring, checking, testing, navigation, control and other	3,623	1,058
333	Manufacture of industrial process control equipment	469	183
334	Manufacture of optical instruments and photographic and cinema equipment	471	62
335	Manufacture of watches and clocks and other time instruments	158	29
341	Manufacture of motor vehicles	724	164
342	Manufacture of bodies (coachwork) for motor vehicles; manufacture of trailers and semi-trailers	268	90
343	Manufacture of parts and accessories for motor vehicles and their engines	1,272	230
351	Building and repairing of ships and boats	2,091	619
352	Manufacture of railway and tramway locomotives and rolling stock	1,054	275
353	Manufacture of aircraft and spacecraft	745	72
354	Manufacture of motorcycles and bicycles	108	8
355	Manufacture of other transport equipment	48	16
361	Manufacture of furniture	12,983	4,225
362	Manufacture of jewellery, medals and related articles of precious metals and stones; manufacture of coins	2,601	435
363	Manufacture of musical instruments	89	8
364	Manufacture of sports goods	440	90
365	Manufacture of games and toys	513	110
366	Other manufacturing	1,978	492
371	Recycling of metal waste and scrap	3,895	1427
372	Recycling of nonmetallic trash and scrap	2,448	729
—	Total number of plants	247,934	71,750
		319,684	

Notes: Author's computations, based on the manufacturing portion of the 2014 RUSLANA database from Bureau Van Dijk Electronic Publishing (BvDEP). See Appendix A.1 for additional information on the database, and Appendix A.2 for details on the east-west split. The OKVED classification is based on the 2008 version of the National Industry Classification.

geographic distribution of economic activity in Russia.

To look at the geographic distribution of industries, we further require industry codes for each establishment. Each establishment reports a primary industry code from the National Industry Classification OKVED (OK 029-2007, used from 1/01/2008–1/01/2011), which is similar to the NACE Rev.2 classification at the 4-digit level. We henceforth refer to it as OKVED 2007 or just OKVED for short. We use industry codes for establishments up to the 4-digit level. Although finer levels of industrial classification are reported by a number of companies, this was not legally mandatory prior to 2012. Hence, samples with industry codes beyond the 4-digit level may be of unreliable coverage. The manufacturing sector is delimited by OKVED 15.00.00 to 37.20.70.[17] We thus have a final dataset of 319,684 companies out of the 320,934 that are precisely geocoded and which report industry information. Table 14 provides a detailed breakdown of establishments by 3-digit industry codes and by east-west location status.

A.2. Geocoding and east-west split. We use a geocoding procedure that involves three steps:

(i) First, each establishment's location is geocoded using the Google Maps API engine (see `http://www.google.com/MapsAPI`). The geocoding procedure returned approximate geographic coordinates for about 70% of establishments in the sample, based mainly on the postal code area. Note that this inaccuracy in the geocoding can be of the order of about 2–3 kilometers. The fact that only about 20% of the establishments were rooftop geocoded using Google can be due to human mistakes (mistakes in postal codes, house numbers, noise in the address information like office numbers), changes in street names and numbers, an inadequate treatment of the building numbers by Google, or—most likely—ambiguities and errors in the translation from the Cyrillic to the roman alphabet.

(ii) Second, we repeat the geocoding based on the romanized versions of the addresses but using the Russian map API provided by Yandex (see `http://tech.yandex.ru/maps`). The Yandex geocoding service provides a finer geographical coverage of Russian localities compared to Google. Yet, the Yandex map API calls do not allow for postal code parameters, which can lead to multiple results (in different regions) for the same street address. To take advantage of both geocoding engines, we utilize the geographic coordinates received in step (i) as centroids and construct 55 kilometer buffers around them. We then explicitly restricting the Yandex search among the localities contained in those buffers. In that case, 66% of the establishments are exactly geocoded with rooftop precision. Only few establishments are not assigned coordinates with a precision of at least the street number.

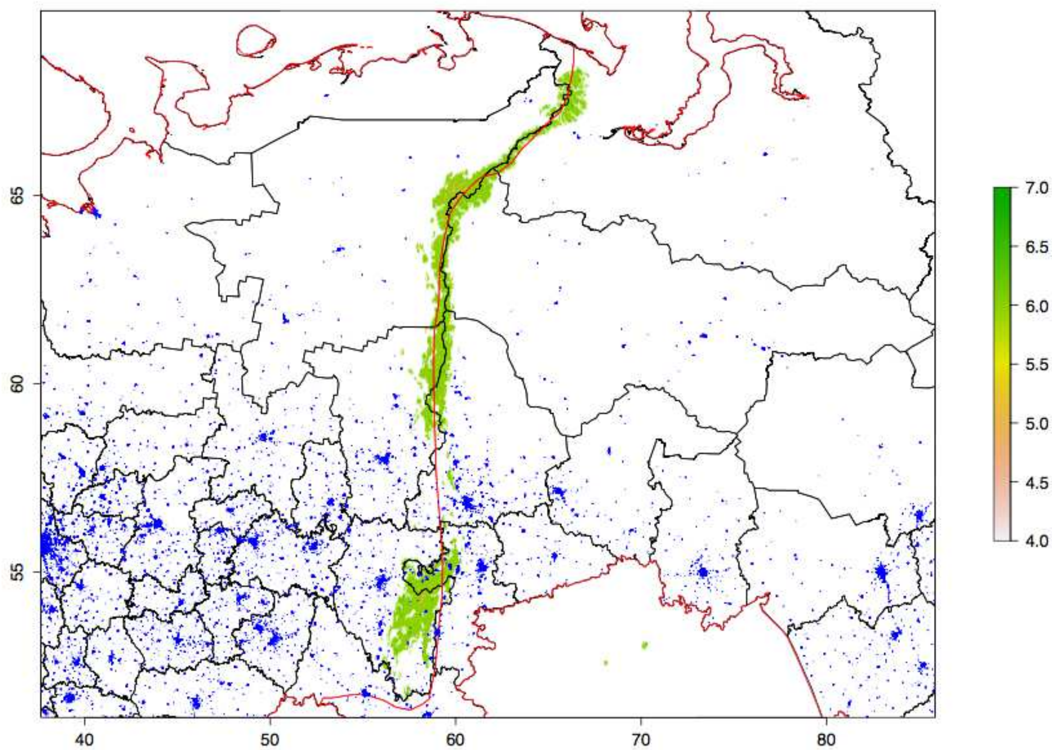
(iii) Last, we run a geocoding procedure based on the Cyrillic versions of the addresses, which have been retranslated from their romanized spelling in the original dataset. We again use the Russian map API provided by Yandex. As expected, this procedure yields a worse suc-

[17] For a small number of establishments, we only have industry information at the 2-digit level. We keep those establishments and group them into their 2-digit industry. These results should be read with caution.

cess rate, but still allows us to retrieve a number of establishments that could not be geocoded based on romanized names.[18]

We finally keep the following establishments that we consider to be geocoded precisely enough: (i) those that are rooftop coded or approximately (postcode) coded by Google API, and that are at the same time precisely coded by Yandex with a difference of less than 2 kilometers between the two results—we then retain the Yandex coordinates, which we consider to be more accurate in general; and (ii) the establishments that are precisely coded by Google API and not precisely coded by Yandex, in which case we retain the Google coordinates.

Figure 13: East-west split of the European and Asian parts along the Ural mountains.



Turning to the east-west split of our sample, the elevation map in Figure 13 shows that the Ural mountain range forms a natural north-south boundary between the Asian and the European parts of Russia.[19] We thus use it to split our sample along that line. Note that the northern part of the Ural mountains runs along the boundary between the regions of the Republic of Komi in the west, and Yamalo-Nenets and the Khanty-Mansiisk autonomous

[18]Although the original Cyrillic names do seem to be available in the Ruslana database, switching to 'English' in the options leads to a download where the names are automatically translated using the Roman alphabet. We noticed this only later once the download and geocoding had been done.

[19]This map is provided by the UN Environment World Conservation Monitoring Centre (`http://datadownload.unep-wcmc.org/?dataset=Mountains_and_Forests_in_Mountains_2000`). The green areas correspond to zones with elevation between 1,000 and 1,500 meters and with a slope of more that 5 degrees or with a local (7 km radius) elevation range in excess of 300 meters.

districts in the east. Whereas the northern part of the mountains follows the administrative boundaries, this is no longer the case in the middle and southern parts. There, the mountains run through the Bashkortostan, Orenburg, Chelyabinsk, Perm, and Sverdlovsk regions. There is no clear cut along administrative lines. This shows that the east-west split can only be meaningfully implemented with detailed microgeographic data.

We use data from the Natural Earth Data page (see `http//www.naturalearthdata.com/download/10m/cultural/ne_10m_admin_0_scale_rank.zip`) to split Russia along the Ural. To this end, we dissolve the polygons for Russia by identifier 'RUE', which are related to the European Part, and by identifier 'RUA', which are related to the Asian Part. Figure 1 shows the north-south division of Russia along the Ural into its eastern and western parts. Using that division, we create an indicator east-west for each plant in our dataset.

B. Ad valorem transport costs and proxies for Marshallian covariates.

In the absence of (reliable) Russian data on the Marshallian covariates, we use different high-quality Canadian and U.S. data to construct our explanatory variables. We first explain how we link the NAICS 4-digit classification used in North America to the Russian OKVED 3-digit classification. We then detail our data and data sources.

B.1. Crosswalk between OKVED 3-digit and NAICS 4-digit industries. The 2008 OKVED 3-digit classification—with 113 manufacturing industries—and the 2002 NAICS 4-digit classification—with 86 manufacturing industries—are broadly comparable.

We classify sectoral matches into four categories (which correspond to the indicator 'flag' in Table 15). First, there are sectors in either the NAICS or the OKVED classification that have no obvious matching counterpart. These include NAICS 3113 ('Sugar and Confectionery Product Manufacturing'), 3118 ('Bakeries and Tortilla Manufacturing'), 3141 ('Textile Furnishings Mills'), 3313 ('Alumina and Aluminum Production and Processing'), 3325 ('Hardware Manufacturing'), 3327 ('Machine Shops, Turned Product, and Screw, Nut and Bolt Manufacturing'), 3334 ('Ventilation, Heating, Air-Conditioning and Commercial Refrigeration Equipment Manufacturing'), (3335, 'Metalworking Machinery Manufacturing'), 3344 ('Semiconductor and Other Electronic Component Manufacturing'); and OKVED 371 ('Recycling of metal waste and scrap'), 372 ('Recycling of nonmetallic trash and scrap'), 233 ('Processing of nuclear fuel'), 267 ('Cutting, shaping and finishing of decorative and building stone'), 174 ('Manufacture of made-up textile articles, except apparel'), 221 ('Publishing'). We flag these sectors with 0. We also flag all sectors that contain 'other' or 'not elsewhere classified' with 0. Those sectors, even when they have very similar names, are likely to have a different composition across classifications (since they are fairly heterogeneous residual categories). Second, there are sectors where either many OKVED match to one NAICS or the other way round. We flag those with 2 or 3 (depending on the direction of the one-to-many correspondence) and try to match the best we can. These sectors will be included or excluded in the analysis to check the robustness of the results. There are also a small number of many-to-many correspondences. Since there is no satisfying way to deal with them, we flag them with 0 and will exclude them. Finally, there is a fairly exact correpondence between about half of the sectors based on the sectors' names. One such example is NAICS 3115 ('Dairy Product Manufacturing') and OKVED 155 ('Manufacture of dairy products'). These 'exact matches' are flagged with 1. We will use these as the baseline since we believe that our covariates for Canada and the U.S. match those sectors reasonably well.

Table 15 provides the full crosswalk that we use. There are 46 exact matches, 32 one-to-many matches (in either direction), and 33 matches that we exclude (based on many-to-many, or the absence of matches, or 'not elsewhere classified' categories). This leaves us with 78 matches in total, 46 of which are good matches.

B.2. Trucking Commodity Origin Destination Survey. We use a series of recent ad valorem transport cost measures developed by Brown (2015) and used by Behrens et al. (2018) and Behrens and Brown (2018). These *ad valorem* rate series are estimated using Statistics Canada's Trucking Commodity Origin-Destination Survey (TCOD). The TCOD is a for-hire carrier-based survey that collects data on a per shipment basis, including the origin and destination, (network) distance shipped, revenue to the carrier, tonnage, and the commodity of the shipment. In order to calculate ad valorem rates, the value of the shipment is also required. Unfortunately, the TCOD does not report the value of goods shipped. Hence, value per tonne estimates by 6-digit Harmonized System (HS) commodity from an 'experiment export trade file' produced in 2008 is used to estimate the value of the shipments. Commodity export price indices are used to project the value per tonne estimates through time (see Brown, 2015, for details). The commodity value per tonne estimates are used to estimate the value of shipments.

This 'augmented' TCOD file is the basis that is used to estimate ad valorem trucking rates by industry. This particular analysis requires a long time period to improve the accuracy of the predicted rates, and the estimates are based on survey weights that ensure trucking rates are representative of the population of carriers. See Brown (2015) and Behrens and Brown (2018) for additional details. We use the ad valorem transport costs (AVTC) for the year 2008, the last year available in the data.

B.3. Input-output coefficients. We use the 2010 input-output matrix for Canada. The finest public release of the input-output matrices is at the L-level (link level), which is between NAICS 3- and 4-digit. We disaggregated the matrix to the W-level (NAICS 6-digit) using either sales or employment data as sectoral weights. We use the input-output tables at buyers' prices. For each manufacturing industry, i, we allocate inputs purchased or outputs sold in the L-level matrix (at the 3- or 4-digit level) to the corresponding NAICS 6-digit subsectors. To do so, we allocate the total sales of each sector to all subsectors in proportion to those sectors' sales in the total sales to obtain a 257×257 matrix of NAICS 6-digit inputs and outputs for manufacturing. We reaggregate these matrices to the 4-digit level to compute the shares that sectors buys from and sell to each other. The input-output shares for the manufacturing submatrix are rescaled to sum to unity.

To make our input-output measures symmetric, for the industry pairs ij and ji we take either the maximum of the respective coefficients or their (simple) average. Hence, in our coagglomeration regressions the input coefficient for industries ij is the maximum of the two input coefficients ij and ji. We do the same for the output coefficients. See Ellison et al. (2010), for additional details and discussion.

B.4. Occupational employment similarity. We compute measures of worker similarity in the different industries. To this end, we use U.S. Occupational Employment Survey (OES) data from the *Bureau of Labor Statistics* for 2011 to compute the share of each of 554 occupations in each 4-digit NAICS industry. We only retain occupations for which there is at least some employment in manufacturing (e.g., there are no 'Surgeons' in manufacturing industries, hence we exclude them completely from our data). Our measure of occupational employment similarity is computed as the correlation coefficient between the vectors of occupational shares of industries i and j. By construction, this measure is symmetric in ij and ji.

B.5. Patent citations across industries. Last, we construct proxies for 'knowledge spillovers' or 'knowledge sharing' by using the NBER Patent Citation database (which builds on U.S. Patent and Trade Office data) and by following previous work by Kerr (2008). Our proxy for knowledge flows is the maximum of the shares of patents that industry i (or j) manufactures ('make-based') or uses ('use-based') and which originate from the other industry j (or i). We take the maximum of the shares ij and ji to obtain a symmetric measure for each pair.

Table 15: Industry crosswalk between 2002 NAICS 4-digit and 2007 OKVED 3-digit.

NAICS	NAICSname	OKVED	OKVEDname	Flag
3111	Animal Food Manufacturing	157	Manufacture of prepared animal feeds	1
3112	Grain and Oilseed Milling	156	Manufacture of grain mill products, starches and starch products	2
3112	Grain and Oilseed Milling	154	Manufacture of vegetable and animal oils and fats	2
3113	Sugar and Confectionery Product Manufacturing			0
3114	Fruit and Vegetable Preserving and Specialty Food Manufacturing	153	Processing and preserving of potato, fruit and vegetables	1
3115	Dairy Product Manufacturing	155	Manufacture of dairy products	1
3116	Meat Product Manufacturing	151	Production, processing and preserving of meat and meat products	1
3117	Seafood Product Preparation and Packaging	152	Processing and preserving of fish and fish products	1
3118	Bakeries and Tortilla Manufacturing			0
3119	Other Food Manufacturing	158	Manufacture of other food products	0
3121	Beverage Manufacturing	159	Manufacture of beverages	1
3122	Tobacco Manufacturing	160	Manufacture of tobacco products	1
3131	Fibre, Yarn and Thread Mills	171	Spinning of textile fibres	1
3132	Fabric Mills	176	Manufacture of textile fabrics	2
3132	Fabric Mills	172	Weaving manufacture	2
3133	Textile and Fabric Finishing and Fabric Coating	173	Finishing of textiles	1
3141	Textile Furnishings Mills			0
3149	Other Textile Product Mills	175	Manufacture of other textiles	0
3151	Clothing Knitting Mills	177	Manufacture of knitted goods	1
3152	Cut and Sew Clothing Manufacturing	182	Manufacture of other wearing apparel and accessories	3
3159	Clothing Accessories and Other Clothing Manufacturing	182	Manufacture of other wearing apparel and accessories	3
3161	Leather and Hide Tanning and Finishing	191	Tanning and dressing of leather	2
3161	Leather and Hide Tanning and Finishing	183	Dressing and dyeing of fur; manufacture of articles of fur	2
3161	Leather and Hide Tanning and Finishing	181	Manufacture of leather clothes	2
3162	Footwear Manufacturing	193	Manufacture of footwear	1
3169	Other Leather and Allied Product Manufacturing	192	Manufacture of luggage, handbags and the like, saddlery and harness	0
3211	Sawmills and Wood Preservation	201	Sawmilling and planing of wood, impregnation of wood	1
3212	Veneer, Plywood and Engineered Wood Product Manufacturing	202	Manufacture of veneer, plywood, cauls, panels	1
3219	Other Wood Product Manufacturing	203	Manufacture of wooden building constructions, including wooden pre-engineered buildings and millwork	2
3219	Other Wood Product Manufacturing	204	Manufacture of wooden containers	2
3219	Other Wood Product Manufacturing	205	Manufacture of other products of wood; manufacture of articles of cork, straw and plaiting materials	2
3221	Pulp, Paper and Paperboard Mills	211	Manufacture of cellulose, pulp, paper and cardboard	1
3222	Converted Paper Product Manufacturing	212	Manufacture of articles of paper and paperboard	1
3231	Printing and Related Support Activities	222	Printing and service activities related to printing	1
3241	Petroleum and Coal Products Manufacturing	231	Manufacture of coke oven products	2
3241	Petroleum and Coal Products Manufacturing	232	Manufacture of refined petroleum products	2
3251	Basic Chemical Manufacturing	241	Manufacture of basic chemicals	1
3252	Resin, Synthetic Rubber, and Artificial and Synthetic Fibres and Filaments Manufacturing	247	Manufacture of artificial and synthetic fibres	1
3253	Pesticide, Fertilizer and Other Agricultural Chemical Manufacturing	242	Manufacture of pesticides and other agro-chemical products	1
3254	Pharmaceutical and Medicine Manufacturing	244	Manufacture of pharmaceuticals	1
3255	Paint, Coating and Adhesive Manufacturing	243	Manufacture of paints and varnishes	1
3256	Soap, Cleaning Compound and Toilet Preparation Manufacturing	245	Manufacture of soap, cleaning and polishing preparations, perfumes and toilet preparations	1
3259	Other Chemical Product Manufacturing	246	Manufacture of other chemical products	0
3261	Plastic Product Manufacturing	252	Manufacture of plastic products	1
3262	Rubber Product Manufacturing	251	Manufacture of rubber products	1
3271	Clay Product and Refractory Manufacturing	262	Manufacture of ceramic goods not used in construction	0
3271	Clay Product and Refractory Manufacturing	263	Manufacture of ceramic tiles and flags	0
3271	Clay Product and Refractory Manufacturing	264	Manufacture of bricks, tiles and construction products, in baked clay	0
3272	Glass and Glass Product Manufacturing	261	Manufacture of glass and glass products	1
3273	Cement and Concrete Product Manufacturing	265	Manufacture of cement, lime and plaster	0
3273	Cement and Concrete Product Manufacturing	266	Manufacture of articles of concrete, plaster or cement	0
3274	Lime and Gypsum Product Manufacturing	265	Manufacture of cement, lime and plaster	0
3279	Other Non-Metallic Mineral Product Manufacturing	268	Manufacture of other non-metallic mineral products	0
3311	Iron and Steel Mills and Ferro-Alloy Manufacturing	271	Manufacture of crude iron, ferroalloy, steel	1
3312	Steel Product Manufacturing from Purchased Steel	272	Manufacture of crude iron and steel pipes	1
3313	Alumina and Aluminum Production and Processing			0
3314	Non-Ferrous Metal (except Aluminum) Production and Processing	274	Manufacture of non-ferrous metals	1

Table 15 (continued).

NAICS	NAICSname	OKVED	OKVEDname	Flag
3315	Foundries	275	Casting of metals	2
3315	Foundries	273	Cast iron and steel other primary processing	2
3321	Forging and Stamping	284	Forging, pressing, stamping and roll forming of metal; powder metallurgy	1
3322	Cutlery and Hand Tool Manufacturing	286	Manufacture of cutlery, tools and general hardware	1
3323	Architectural and Structural Metals Manufacturing	281	Manufacture of constructional metal products	1
3324	Boiler, Tank and Shipping Container Manufacturing	282	Manufacture of metal tanks, reservoirs and containers; manufacture of central heating radiators and boilers	1
3325	Hardware Manufacturing			0
3326	Spring and Wire Product Manufacturing	313	Manufacture of insulated wire and cable	1
3327	Machine Shops, Turned Product, and Screw, Nut and Bolt Manufacturing			0
3328	Coating, Engraving, Heat Treating and Allied Activities	285	Treatment and coating of metals; general mechanical engineering	1
3329	Other Fabricated Metal Product Manufacturing	287	Manufacture of other fabricated metal products	2
3329	Other Fabricated Metal Product Manufacturing	296	Manufacture of weapons and ammunition	2
3331	Agricultural, Construction and Mining Machinery Manufacturing	293	Manufacture of agricultural and forestry machinery	1
3332	Industrial Machinery Manufacturing	294	Manufacture of machine-tools	0
3333	Commercial and Service Industry Machinery Manufacturing	291	Manufacture of machinery	0
3333	Commercial and Service Industry Machinery Manufacturing	334	Manufacture of optical instruments and photographic and cinema equipment	0
3333	Commercial and Service Industry Machinery Manufacturing	295	Manufacture of other special purpose machinery	0
3334	Ventilation, Heating, Air-Conditioning and Commercial Refrigeration Equipment Manufacturing			0
3335	Metalworking Machinery Manufacturing			0
3336	Engine, Turbine and Power Transmission Equipment Manufacturing	283	Manufacture of steam generators, except central heating hoboilers; manufacture of nuclear reactors	0
3339	Other General-Purpose Machinery Manufacturing	292	Manufacture of other general purpose machinery	1
3341	Computer and Peripheral Equipment Manufacturing	300	Manufacture of office machinery and computers	1
3342	Communications Equipment Manufacturing			0
3343	Audio and Video Equipment Manufacturing	321	Manufacture of electronic and radio components, electrovacuum devices	2
3343	Audio and Video Equipment Manufacturing	322	Manufacture of television and radio transmitters and apparatus for electric communications	2
3343	Audio and Video Equipment Manufacturing	323	Manufacture of television and radio receivers, sound or video recording or reproducing apparatus and associated goods	2
3344	Semiconductor and Other Electronic Component Manufacturing			0
3345	Navigational, Measuring, Medical and Control Instruments Manufacturing	332	Manufacture of instruments and appliances for measuring, checking, testing, navigation, control and other	2
3345	Navigational, Measuring, Medical and Control Instruments Manufacturing	333	Manufacture of industrial process control equipment	2
3345	Navigational, Measuring, Medical and Control Instruments Manufacturing	335	Manufacture of watches and clocks and other time instruments	2
3346	Manufacturing and Reproducing Magnetic and Optical Media	223	Reproduction of recorded media	1
3351	Electric Lighting Equipment Manufacturing	315	Manufacture of lighting equipment and electric lamps	1
3352	Household Appliance Manufacturing	297	Manufacture of domestic appliances n	1
3353	Electrical Equipment Manufacturing	312	Manufacture of electricity distribution and control apparatus	2
3353	Electrical Equipment Manufacturing	311	Manufacture of electric motors, generators and transformers	2
3353	Electrical Equipment Manufacturing	314	Manufacture of accumulators, primary cells and primary batteries	2
3359	Other Electrical Equipment and Component Manufacturing	316	Manufacture of other electrical equipment n	0
3361	Motor Vehicle Manufacturing	341	Manufacture of motor vehicles	2
3361	Motor Vehicle Manufacturing	354	Manufacture of motorcycles and bicycles	2
3362	Motor Vehicle Body and Trailer Manufacturing	342	Manufacture of bodies (coachwork) for motor vehicles; manufacture of trailers and semi-trailers	1
3363	Motor Vehicle Parts Manufacturing	343	Manufacture of parts and accessories for motor vehicles and their engines	1
3364	Aerospace Product and Parts Manufacturing	353	Manufacture of aircraft and spacecraft	1
3365	Railroad Rolling Stock Manufacturing	352	Manufacture of railway and tramway locomotives and rolling stock	1
3366	Ship and Boat Building	351	Building and repairing of ships and boats	1
3369	Other Transportation Equipment Manufacturing	355	Manufacture of other transport equipment n	0
3371	Household and Institutional Furniture and Kitchen Cabinet Manufacturing	361	Manufacture of furniture	3
3372	Office Furniture (including Fixtures) Manufacturing	361	Manufacture of furniture	3
3379	Other Furniture-Related Product Manufacturing	361	Manufacture of furniture	3
3391	Medical Equipment and Supplies Manufacturing	331	Manufacture of medical and surgical equipment and orthopaedic appliances	1
3399	Other Miscellaneous Manufacturing	362	Manufacture of jewellery, medals and related articles of precious metals and stones; manufacture of coins	0
3399	Other Miscellaneous Manufacturing	363	Manufacture of musical instruments	0
3399	Other Miscellaneous Manufacturing	364	Manufacture of sports goods	0
3399	Other Miscellaneous Manufacturing	366	Other manufacturing n	0
3399	Other Miscellaneous Manufacturing	365	Manufacture of games and toys	0

Notes: Crosswalk between the 2002 NAICS 4-digit and the 2008 OKVED 3-digit industry classifications. The field 'flag' contains the following information: 0 = no correspondence or industries containing 'others' or 'not elsewhere classified (n)'; 1 = one-to-one correspondence; 2 = many-to-one correspondence. We do not report industries for which there is no approximate correspondence in the other classification (see Appendix B.1 for a list of these industries).

Supplemental online appendix

This appendix is not intended for publication. It contains additional results and robustness checks.

S.1. Additional comparisons of the different samples.

Our key findings are fairly robust to the use of the small, medium, or large sample of establishments. Table 16 shows summary statistics for the different K-density CDFS. Clearly, the results are very similar on average, even if the large sample tends to produce slightly stronger agglomeration patterns than the medium or the small samples. Figure 14 further breaks down the correlations between the CDFS by distance. As shown, the correlations are uniformly high, except at fairly short distances (below 50 kilometers) for the small sample at the OKVED 4-digit level in eastern Russia.

Table 17 summarizes information as to how many industries change their localization status across the different samples. Note first that, as shown by the top panel of the table, there are generally few 'significant changes', i.e., changes between dispersed and localized. This is especially true between the medium and the large samples. There are, however, a larger share of significant changes going from the medium (or the large) to the small sample. The same pattern holds for 'marginal changes', i.e., changes between either dispersed or localized and random.

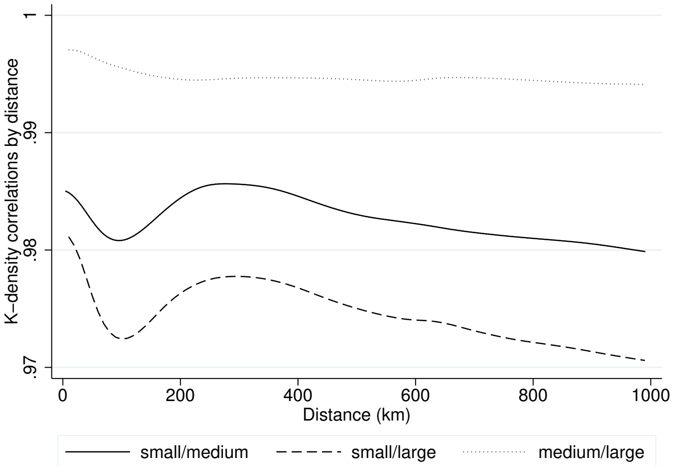
When taken together, the results summarize in Tables 16 and 17 and in Figure 14 suggest that our results are robust to the choice of the large or the medium-sized samples, and somewhat less robust to the choice of the small sample. We hence restrict most of our analysis to the large and medium-sized samples.

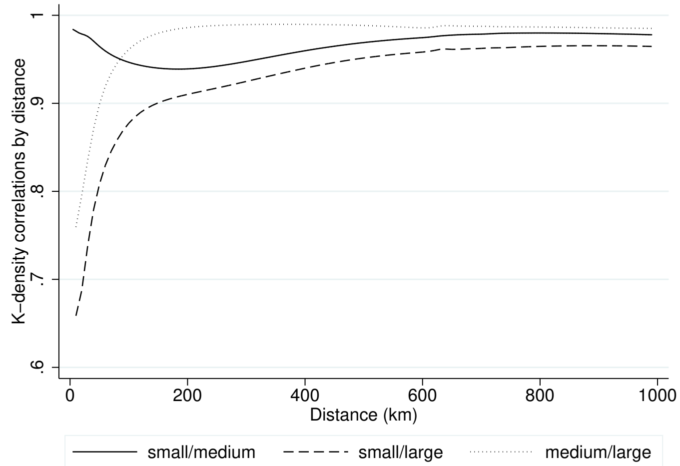
S.2. Additional tables and results.

Figure 14: Correlations between the small/medium/large sample CDFS, by distance.

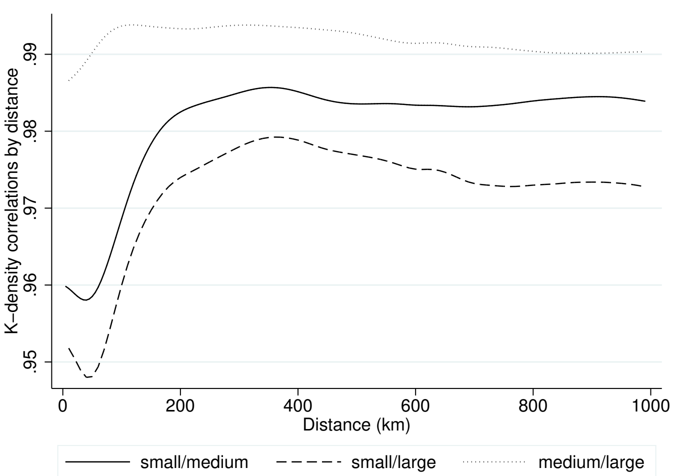
(a) OKVED 3-digit. (b) OKVED 4-digit.

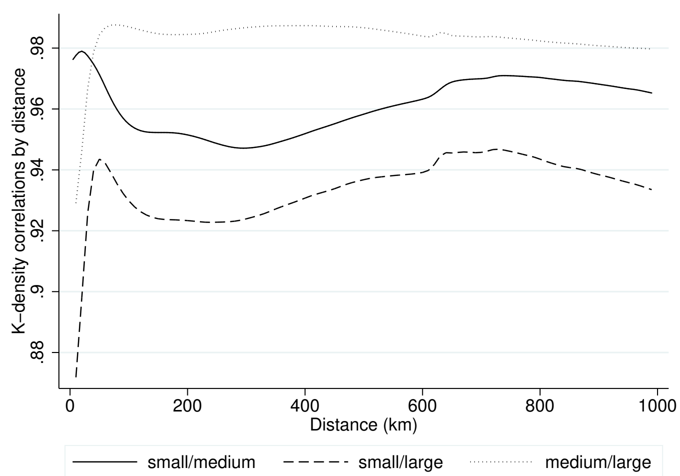
(1) Whole of Russia.



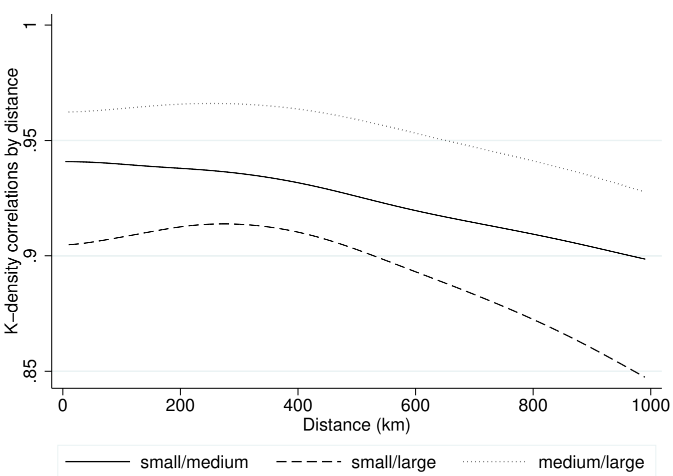


(2) Western Russia.





(3) Eastern Russia.



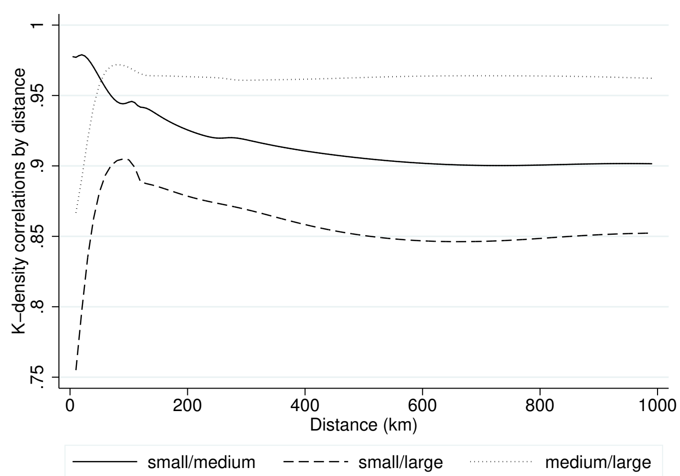


Table 16: Descriptive statistics for the small/medium/large samples.

K-density CDF			Observations	Mean	Std dev.	Min	Max
Sample	Geography	Step size	**OKVED 4-digit industries**				
Large	Whole of Russia	10km	29,600	0.274	0.169	0	0.929
Medium	Whole of Russia	5km	59,200	0.273	0.170	0	0.934
Small	Whole of Russia	1km	296,000	0.271	0.171	0	0.910
Large	Western Russia	10km	29,600	0.388	0.220	0	0.982
Medium	Western Russia	5km	59,200	0.385	0.220	0	0.995
Small	Western Russia	1km	296,000	0.381	0.220	0	1.000
Large	Eastern Russia	10km	27,900	0.259	0.156	0	0.889
Medium	Eastern Russia	5km	54,600	0.259	0.158	0	0.980
Small	Eastern Russia	1km	263,000	0.255	0.161	0	1.000
			OKVED 3-digit industries				
Large	Whole of Russia	10km	10,300	0.270	0.162	0	0.784
Medium	Whole of Russia	5km	20,600	0.269	0.162	0	0.795
Small	Whole of Russia	1km	103,000	0.266	0.162	0	.790
Large	Western Russia	10km	10,300	0.386	0.215	0	0.888
Medium	Western Russia	5km	20,600	0.383	0.215	0	0.889
Small	Western Russia	1km	103,000	0.378	0.214	0	0.878
Large	Eastern Russia	10km	10,300	0.240	0.137	0	0.637
Medium	Eastern Russia	5km	20,600	0.241	0.137	0	0.625
Small	Eastern Russia	1km	103,000	0.234	0.139	0	0.653

Notes: Results for 296 4-digit industries, and 103 3-digit industries. The number of observations depend on the industry level and the step size. For example, for 3-digit OKVED and the large sample there are 10,300 observations (103 industries, and 100 steps (from 0 to 100km in 10km increments).

Table 17: Number of industries with changing localization status, all samples.

	Type and size of the sample					
	Whole of Russia		Western Russia		Eastern Russia	
Change	L → M	M → S	L → M	M → S	L → M	M → S
	OKVED **4-digit industries**					
	Significant changes					
dispersed → localized	3		3	3	1	1
localized → dispersed	2	9	7	10	4	1
	Marginal changes					
random → localized	2	3	4	6	5	2
random → dispersed		1	1	3	1	1
localized → random	10	16	15	18	14	23
dispersed → random	3	10	9	11	3	3
	Summary of changes					
# of change	20	39	39	51	28	31
# of stable	276	257	257	245	245	232
Total industries	296	296	296	296	273	263
	OKVED **3-digit industries**					
	Significant changes					
dispersed → localized	1			2		
localized → dispersed	2	7	3	8	1	2
	Marginal changes					
random → localized		1	1		1	
random → dispersed		1			2	1
localized → random	3	2	2	2	4	8
dispersed → random	1	1	1	2	1	4
	Summary of changes					
# of change	7	12	7	14	9	15
# of stable	96	91	96	89	94	88
Total industries	103	103	103	103	103	103

Notes: Small sample (S) = 2014; medium sample (M) = 2013 and 2014; large sample (L) = 2012, 2013, and 2014. L → M indicates changes between the large and the medium sample; M → S indicates changes between the medium and the small sample.

Table 18: Top-10 *most localized* industries, all of Russia (OKVED 3-digit).

OKVED	Industry name	# of plants	Γ_A
Small sample			
172	Weaving manufacture	384	0.278
176	Manufacture of textile fabrics	61	0.276
223	Reproduction of recorded media	272	0.258
244	Manufacture of pharmaceuticals	1338	0.217
171	Spinning of textile fibres	276	0.186
362	Manufacture of jewellery, medals and related articles of precious metals and stones; manufacture of coins	1757	0.184
353	Manufacture of aircraft and spacecraft	465	0.181
321	Manufacture of electronic and radio components, electrovacuum devices	615	0.169
300	Manufacture of office machinery and computers	1437	0.168
335	Manufacture of watches and clocks and other time instruments	114	0.163
Medium sample			
172	Weaving manufacture	565	0.314
223	Reproduction of recorded media	384	0.280
353	Manufacture of aircraft and spacecraft	707	0.262
176	Manufacture of textile fabrics	94	0.237
244	Manufacture of pharmaceuticals	1849	0.214
171	Spinning of textile fibres	402	0.205
321	Manufacture of electronic and radio components, electrovacuum devices	831	0.201
362	Manufacture of jewellery, medals and related articles of precious metals and stones; manufacture of coins	2432	0.201
173	Finishing of textiles	335	0.185
300	Manufacture of office machinery and computers	2021	0.185
Large sample			
172	Weaving manufacture	699	0.305
353	Manufacture of aircraft and spacecraft	817	0.270
223	Reproduction of recorded media	487	0.254
244	Manufacture of pharmaceuticals	2259	0.224
173	Finishing of textiles	426	0.200
362	Manufacture of jewellery, medals and related articles of precious metals and stones; manufacture of coins	3036	0.199
176	Manufacture of textile fabrics	119	0.191
321	Manufacture of electronic and radio components, electrovacuum devices	1004	0.178
300	Manufacture of office machinery and computers	2605	0.176
171	Spinning of textile fibres	495	0.173

Notes: Γ_A is computed at 990km, 995km and 999km (the last point at which the K-densities are evaluated) for the large, the medium, and the small samples, respectively. We hence measure localization over the whole distance range that we compute the K-densities for.

Table 19: Top-10 *most geographically concentrated* industries, all of Russia (OKVED 3-digit).

OKVED	Industry name	# of plants	CDF
Small sample			
244	Manufacture of pharmaceuticals	1,338	0.170
223	Reproduction of recorded media	272	0.140
221	Publishing	13,260	0.135
300	Manufacture of office machinery and computers	1,437	0.128
362	Manufacture of jewellery, medals and related articles of precious metals and stones; manufacture of coins	1,757	0.119
353	Manufacture of aircraft and spacecraft	465	0.109
176	Manufacture of textile fabrics	61	0.107
172	Weaving manufacture	384	0.101
321	Manufacture of electronic and radio components, electrovacuum devices	615	0.095
222	Printing and service activities related to printing	8,252	0.094
Medium sample			
244	Manufacture of pharmaceuticals	1,849	0.178
353	Manufacture of aircraft and spacecraft	707	0.169
223	Reproduction of recorded media	384	0.159
300	Manufacture of office machinery and computers	2,021	0.148
221	Publishing	18,728	0.142
362	Manufacture of jewellery, medals and related articles of precious metals and stones; manufacture of coins	2,432	0.134
172	Weaving manufacture	565	0.120
321	Manufacture of electronic and radio components, electrovacuum devices	831	0.110
176	Manufacture of textile fabrics	94	0.108
222	Printing and service activities related to printing	11,995	0.106
Large sample			
244	Manufacture of pharmaceuticals	2,259	0.191
353	Manufacture of aircraft and spacecraft	817	0.178
223	Reproduction of recorded media	487	0.159
300	Manufacture of office machinery and computers	2,605	0.156
221	Publishing	23,735	0.148
362	Manufacture of jewellery, medals and related articles of precious metals and stones; manufacture of coins	3,036	0.141
172	Weaving manufacture	699	0.122
173	Finishing of textiles	426	0.115
222	Printing and service activities related to printing	15,194	0.114
321	Manufacture of electronic and radio components, electrovacuum devices	1,004	0.112

Notes: We report the CDF of the K-density at a distance of $d = 50$km. Hence, the values summarize the share of bilateral distances between pairs of establishments in the industry that is below 50 kilometers.

Figure 15: Skewness of the strength of localization and K-density CDF (large sample, OKVED 3-digit).

(1) Western Russia. (2) Eastern Russia.

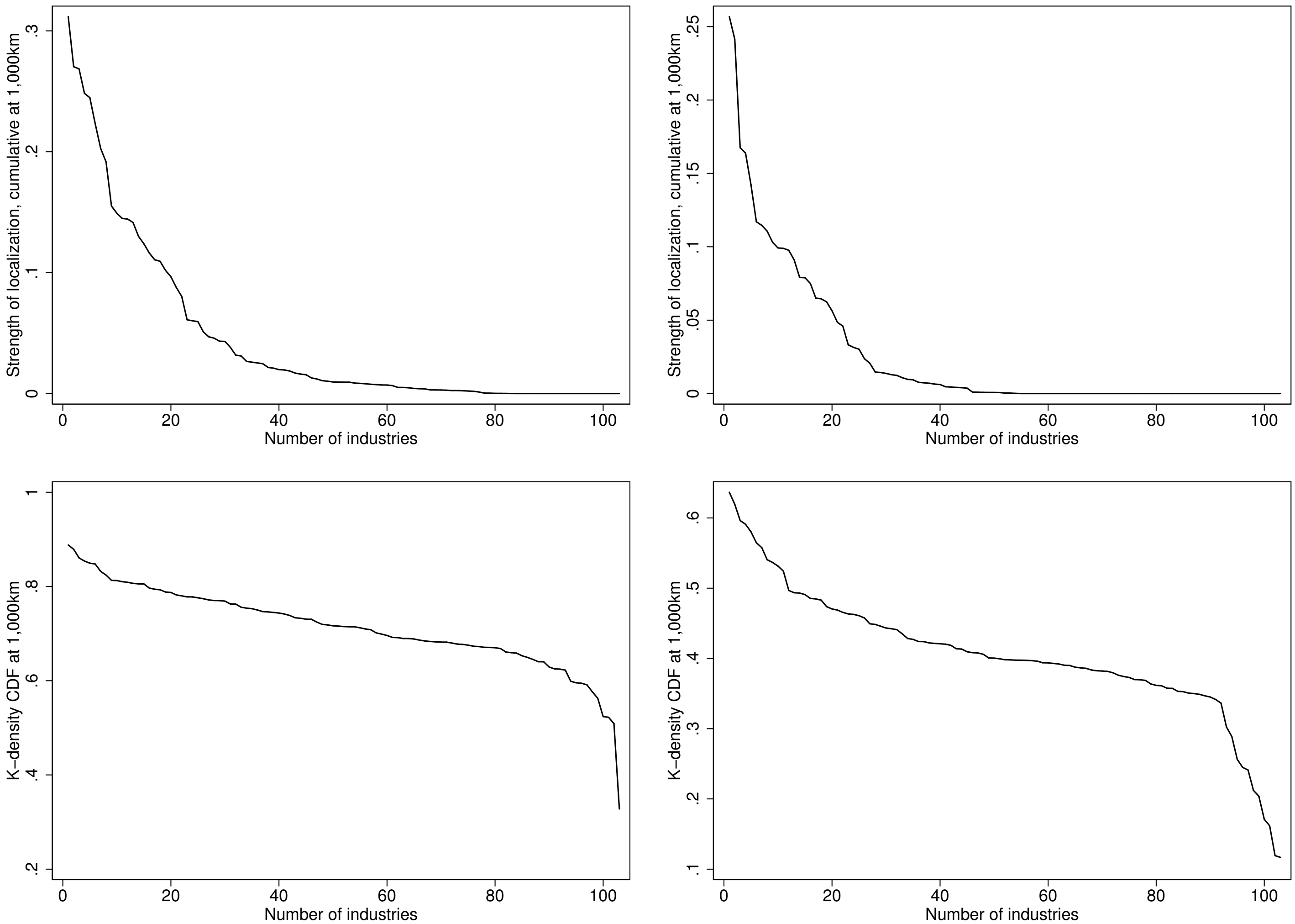


Table 20: Top-10 *least localized* industries (OKVED 4-digit, large samples).

OKVED	Industry name	# of plants	Ψ_A
	All of Russia		
1520	Processing and preserving of fish and fish products	2,549	0.149
3511	Building and repairing of ships	2,002	0.107
1598	Production of mineral waters and soft drinks	2,562	0.088
1596	Manufacture of beer	898	0.079
2212	Publishing of newspapers	4,457	0.070
2661	Manufacture of concrete products for construction purposes	5,473	0.070
1581	Manufacture of bread; manufacture of fresh pastry goods and cakes	7,170	0.060
2952	Manufacture of machinery for mining, quarrying and construction	961	0.049
2640	Manufacture of bricks, tiles and construction products, in baked clay	1,673	0.049
2411	Manufacture of industrial gases	595	0.044
	Western Russia		
1598	Production of mineral waters and soft drinks	1,877	0.102
1520	Processing and preserving of fish and fish products	1,633	0.085
1591	Manufacture of distilled potable alcoholic beverages	332	0.081
1596	Manufacture of beer	623	0.077
2663	Manufacture of ready-mixed concrete	1,679	0.060
2411	Manufacture of industrial gases	411	0.045
2320	Manufacture of refined petroleum products	1,330	0.039
3510	Building and repairing of ships and boats	310	0.035
3661	Manufacture of imitation jewellery	78	0.029
1532	Manufacture of fruit and vegetable juice	236	0.028
	Eastern Russia		
1598	Production of mineral waters and soft drinks	685	0.045
3622	Manufacture of jewellery and related articles of precious metals and stones	398	0.039
2411	Manufacture of industrial gases	184	0.027
2663	Manufacture of ready-mixed concrete	463	0.017
2221	Printing of newspapers	155	0.013
2210	Publishing	1,711	0.012
1596	Manufacture of beer	275	0.010
2661	Manufacture of concrete products for construction purposes	1,519	0.009
2911	Manufacture of engines and turbines, except aircraft, jet, vehicle and cycles engines	186	0.007
2640	Manufacture of bricks, tiles and construction products, in baked clay	414	0.005

Notes: Ψ_A is computed at 990km, 995km and 999km (the last point at which the K-densities are evaluated) for the large, the medium, and the small samples, respectively. We hence measure localization over the whole distance range that we compute the K-densities for.

Table 21: Top-10 *most dispersed* industries (OKVED 3-digit, large sample).

OKVED	Industry name	# of plants	CDF
	All of Russia		
152	Processing and preserving of fish and fish products	2,549	0.150
351	Building and repairing of ships and boats	2,710	0.089
159	Manufacture of beverages	4,642	0.081
266	Manufacture of articles of concrete, plaster or cement	12,380	0.062
151	Production, processing and preserving of meat and meat products	6,576	0.046
268	Manufacture of other non-metallic mineral products	2,233	0.024
283	Manufacture of steam generators, except central heating hoboilers; manufacture of nuclear reactors	667	0.024
282	Manufacture of metal tanks, reservoirs and containers; manufacture of central heating radiators and boilers	1,491	0.019
153	Processing and preserving of potato, fruit and vegetables	1,762	0.018
157	Manufacture of prepared animal feeds	1,141	0.015
	Western Russia		
159	Manufacture of beverages	3,510	0.108
152	Processing and preserving of fish and fish products	1,633	0.085
153	Processing and preserving of potato, fruit and vegetables	1,377	0.030
157	Manufacture of prepared animal feeds	873	0.029
333	Manufacture of industrial process control equipment	469	0.021
295	Manufacture of other special purpose machinery	3,842	0.002
265	Manufacture of cement, lime and plaster	433	0.001
160	Manufacture of tobacco products	98	0.000
335	Manufacture of watches and clocks and other time instruments	158	0.000
176	Manufacture of textile fabrics	106	0.000
	Eastern Russia		
152	Processing and preserving of fish and fish products	916	0.076
362	Manufacture of jewellery, medals and related articles of precious metals and stones; manufacture of coins	435	0.045
159	Manufacture of beverages	1,132	0.041
266	Manufacture of articles of concrete, plaster or cement	3,218	0.013
232	Manufacture of refined petroleum products	282	0.007
264	Manufacture of bricks, tiles and construction products, in baked clay	414	0.006
341	Manufacture of motor vehicles	164	0.000
154	Manufacture of vegetable and animal oils and fats	227	0.000
275	Casting of metals	202	0.000
272	Manufacture of crude iron and steel pipes	97	0.000

Notes: We report the CDF of the K-density at a distance of $d = 50$km. Hence, the values summarize the share of bilateral distances between pairs of establishments in the industry that is below 50 kilometers.

Table 22: Top 10 *most localized* industries, western Russia (OKVED 3-digit).

OKVED	Industry name	# of plants	Γ_A
Small sample			
223	Reproduction of recorded media	247	0.359
244	Manufacture of pharmaceuticals	1,145	0.273
335	Manufacture of watches and clocks and other time instruments	97	0.238
172	Weaving manufacture	362	0.214
300	Manufacture of office machinery and computers	1,224	0.188
362	Manufacture of jewellery, medals and related articles of precious metals and stones; manufacture of coins	1,514	0.187
173	Finishing of textiles	209	0.159
171	Spinning of textile fibres	251	0.156
353	Manufacture of aircraft and spacecraft	418	0.155
221	Publishing	10,730	0.148
Medium sample			
223	Reproduction of recorded media	346	0.393
353	Manufacture of aircraft and spacecraft	644	0.269
244	Manufacture of pharmaceuticals	1,583	0.267
172	Weaving manufacture	533	0.264
176	Manufacture of textile fabrics	85	0.228
173	Finishing of textiles	293	0.227
362	Manufacture of jewellery, medals and related articles of precious metals and stones; manufacture of coins	2,097	0.218
300	Manufacture of office machinery and computers	1,730	0.202
321	Manufacture of electronic and radio components, electrovacuum devices	741	0.161
171	Spinning of textile fibres	371	0.155
Large sample			
223	Reproduction of recorded media	438	0.312
244	Manufacture of pharmaceuticals	1,943	0.270
353	Manufacture of aircraft and spacecraft	745	0.269
173	Finishing of textiles	373	0.248
172	Weaving manufacture	658	0.245
362	Manufacture of jewellery, medals and related articles of precious metals and stones; manufacture of coins	2,601	0.223
300	Manufacture of office machinery and computers	2,220	0.203
176	Manufacture of textile fabrics	106	0.192
335	Manufacture of watches and clocks and other time instruments	158	0.155
221	Publishing	19,142	0.149

Notes: Γ_A is computed at 990km, 995km and 999km (the last point at which the K-densities are evaluated) for the large, the medium, and the small samples, respectively. We hence measure localization over the whole distance range that we compute the K-densities for.

Table 23: Top 10 *most localized* industries, eastern Russia (OKVED 3-digit).

OKVED	Industry name	# of plants	Γ_A
Small sample			
343	Manufacture of parts and accessories for motor vehicles and their engines	119	0.238
286	Manufacture of cutlery, tools and general hardware	102	0.163
156	Manufacture of grain mill products, starches and starch products	352	0.144
341	Manufacture of motor vehicles	99	0.136
272	Manufacture of crude iron and steel pipes	58	0.136
342	Manufacture of bodies (coachwork) for motor vehicles; manufacture of trailers and semi-trailers	53	0.116
285	Treatment and coating of metals; general mechanical engineering	962	0.108
154	Manufacture of vegetable and animal oils and fats	128	0.098
294	Manufacture of machine-tools	262	0.094
271	Manufacture of crude iron, ferroalloy, steel	172	0.086
Medium sample			
343	Manufacture of parts and accessories for motor vehicles and their engines	182	0.225
341	Manufacture of motor vehicles	142	0.192
271	Manufacture of crude iron, ferroalloy, steel	261	0.155
272	Manufacture of crude iron and steel pipes	82	0.136
283	Manufacture of steam generators, except central heating hoboilers; manufacture of nuclear reactors	190	0.126
154	Manufacture of vegetable and animal oils and fats	190	0.109
285	Treatment and coating of metals; general mechanical engineering	1,399	0.107
156	Manufacture of grain mill products, starches and starch products	509	0.106
342	Manufacture of bodies (coachwork) for motor vehicles; manufacture of trailers and semi-trailers	77	0.105
294	Manufacture of machine-tools	382	0.091
Large sample			
341	Manufacture of motor vehicles	164	0.257
343	Manufacture of parts and accessories for motor vehicles and their engines	230	0.241
271	Manufacture of crude iron, ferroalloy, steel	314	0.167
272	Manufacture of crude iron and steel pipes	97	0.164
342	Manufacture of bodies (coachwork) for motor vehicles; manufacture of trailers and semi-trailers	90	0.142
156	Manufacture of grain mill products, starches and starch products	597	0.117
285	Treatment and coating of metals; general mechanical engineering	1,764	0.115
275	Casting of metals	202	0.111
294	Manufacture of machine-tools	479	0.103
154	Manufacture of vegetable and animal oils and fats	227	0.099

Notes: Γ_A is computed at 990km, 995km and 999km (the last point at which the K-densities are evaluated) for the large, the medium, and the small samples, respectively. We hence measure localization over the whole distance range that we compute the K-densities for.

Table 24: Top 10 *most geographically concentrated* industries, western Russia (OKVED 3-digit).

OKVED	Industry name	# of plants	CDF
Small sample			
244	Manufacture of pharmaceuticals	1,145	0.296
223	Reproduction of recorded media	247	0.292
221	Publishing	10,730	0.227
335	Manufacture of watches and clocks and other time instruments	97	0.223
300	Manufacture of office machinery and computers	1,224	0.187
362	Manufacture of jewellery, medals and related articles of precious metals and stones; manufacture of coins	1,514	0.166
222	Printing and service activities related to printing	6,632	0.164
173	Finishing of textiles	209	0.149
353	Manufacture of aircraft and spacecraft	418	0.145
331	Manufacture of medical and surgical equipment and orthopaedic appliances	1,628	0.138
Medium sample			
223	Reproduction of recorded media	346	0.355
244	Manufacture of pharmaceuticals	1,583	0.293
353	Manufacture of aircraft and spacecraft	644	0.263
221	Publishing	15,109	0.233
173	Finishing of textiles	293	0.219
300	Manufacture of office machinery and computers	1,730	0.213
362	Manufacture of jewellery, medals and related articles of precious metals and stones; manufacture of coins	2,097	0.194
222	Printing and service activities related to printing	9,629	0.180
176	Manufacture of textile fabrics	85	0.159
331	Manufacture of medical and surgical equipment and orthopaedic appliances	2,337	0.152
Large sample			
244	Manufacture of pharmaceuticals	1,943	0.307
223	Reproduction of recorded media	438	0.290
353	Manufacture of aircraft and spacecraft	745	0.274
173	Finishing of textiles	373	0.240
221	Publishing	19,142	0.238
300	Manufacture of office machinery and computers	2,220	0.229
362	Manufacture of jewellery, medals and related articles of precious metals and stones; manufacture of coins	2,601	0.210
222	Printing and service activities related to printing	12,211	0.190
331	Manufacture of medical and surgical equipment and orthopaedic appliances	2,764	0.166
176	Manufacture of textile fabrics	106	0.162

Notes: We report the CDF of the K-density at a distance of $d = 50$km. Hence, the values summarize the share of bilateral distances between pairs of establishments in the industry that is below 50 kilometers.

Table 25: Top 10 *most geographically concentrated* industries, eastern Russia (OKVED 3-digit).

OKVED	Industry name	# of plants	CDF
Small sample			
343	Manufacture of parts and accessories for motor vehicles and their engines	119	0.084
272	Manufacture of crude iron and steel pipes	58	0.064
286	Manufacture of cutlery, tools and general hardware	102	0.062
341	Manufacture of motor vehicles	99	0.059
285	Treatment and coating of metals; general mechanical engineering	962	0.055
342	Manufacture of bodies (coachwork) for motor vehicles; manufacture of trailers and semi-trailers	53	0.054
154	Manufacture of vegetable and animal oils and fats	128	0.052
271	Manufacture of crude iron, ferroalloy, steel	172	0.051
294	Manufacture of machine-tools	262	0.051
283	Manufacture of steam generators, except central heating hoboilers; manufacture of nuclear reactors	139	0.049
Medium sample			
343	Manufacture of parts and accessories for motor vehicles and their engines	182	0.092
341	Manufacture of motor vehicles	142	0.079
271	Manufacture of crude iron, ferroalloy, steel	261	0.068
272	Manufacture of crude iron and steel pipes	82	0.067
283	Manufacture of steam generators, except central heating hoboilers; manufacture of nuclear reactors	190	0.060
285	Treatment and coating of metals; general mechanical engineering	1,399	0.058
294	Manufacture of machine-tools	382	0.054
342	Manufacture of bodies (coachwork) for motor vehicles; manufacture of trailers and semi-trailers	77	0.054
154	Manufacture of vegetable and animal oils and fats	190	0.053
275	Casting of metals	158	0.049
Large sample			
341	Manufacture of motor vehicles	164	0.100
343	Manufacture of parts and accessories for motor vehicles and their engines	230	0.095
272	Manufacture of crude iron and steel pipes	97	0.070
271	Manufacture of crude iron, ferroalloy, steel	314	0.069
351	Building and repairing of ships and boats	619	0.061
285	Treatment and coating of metals; general mechanical engineering	1,764	0.059
342	Manufacture of bodies (coachwork) for motor vehicles; manufacture of trailers and semi-trailers	90	0.059
294	Manufacture of machine-tools	479	0.056
274	Manufacture of non-ferrous metals	269	0.054
154	Manufacture of vegetable and animal oils and fats	227	0.052

Notes: We report the CDF of the K-density at a distance of $d = 50$km. Hence, the values summarize the share of bilateral distances between pairs of establishments in the industry that is below 50 kilometers.

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