Educational Migration from Russia to the Nordic Countries, China and the Middle East. Social Media Data

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ABSTRACT

We use social media and WWW data to analyse international educational migration from Russia. We find substantial regional differences in migration patterns for three contrast directions: the Nordic countries, China and the Middle East. We built a model of migration flows with geographic distances to destination countries, various socio-demographic data and institutional characteristics of educational organisations.

CCS CONCEPTS

• **Information systems** → **Social networks**; *Web mining*; • **Applied computing** → *Sociology*;

KEYWORDS

educational migration, international students, social media, webometrics

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1 INTRODUCTION

We use social media and web data to study educational migration patterns in Eurasia, in particular, Russia[1] and other former USSR countries (fSU). The data from social networking sites (SNS), such as Facebook or LinkedIn, already yielded new unprecedented results in demographic and migration research[4, 5]. Current research on transnational/cross-border education and international student mobility uses existing government data assembled by international agencies, which allows analysis only at the country level[2, 3]. Our approach using the data from VKontakte (VK), the most popular SNS in the fSU with over 210 million profiles, allows us to study the recent mobility of young people in exceptional detail at the city level – the details unavailable from offline statistics.

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2 DATA AND METHOD

Data collection. To estimate migration rates, we have collected aggregated data on 85,552 VK profiles at a flow level (city–country). The search query included people aged 22–28 years old, who reported their school to be in one of the Russian cities with a population more than 50,000 and tertiary education in another country. We selected 279 Russian cities and 40 destination countries which either are on the list of countries with the highest number of Russian students according to UNESCO data or share a border with Russia. This sample ($N = 489$) was used for the analysis of migration patterns; additional filtering for the regression model excluded cities with population less than 100,000.

Table 1: Variables and Descriptive Statistics

Statistic	Mean	σ	Min	Max
# of ed. migrants for the flow (dependent)	20.4	77.7	0.0	1181.0
Mean distance to the dest. countries (log)	7.7	0.7	2.1	9.0
# of ed. migrants from the city (log)	5.1	1.1	2.8	10.1
% of city pop. self-assoc. w/main dest. religion	3.0	11.7	0.0	96.0
# of "dest.-country" VK groups per mil	0.1	0.1	0.0	1.5
Dist. to nearest 1mln city in Russia (100km)	4.4	7.3	0.0	41.1
Presence of dest. cultural institutions	Yes: 17, No: 472			

Destinations. Our analysis included three destination regions of interest: China, Nordic countries and the Middle East. They have regionally specific patterns of educational migration from Russia. Other countries and regions (Germany, France, UK, USA) do not show regionally specific influence in Russia, with sending cities more or less evenly distributed around the country. In this paper we focus on the distinct patterns within Russia.

China currently is one of the fastest growing destinations for foreign enrolment. It shares an extensive border with Russia in Siberia and the Far East, which are the most underdeveloped territories in Russia. The Nordic countries (Denmark, Finland, Norway and Sweden) are geographically close to the north-western part of Russia with many institutional and ethno-cultural connections. The Middle East direction (Egypt, Iran, Iraq, Jordan, Saudi Arabia, Syria, Turkey, United Arab Emirates) is interesting due to religious and cultural affinity with the populations in particular regions of Russia.

Methods. To explore distinct patterns of migration we used standardized Pearson residuals for the contingency table "region-city" and highlighted zones of regional influence that produce student flows larger than expected based on the proportion.

Figure 1: Map of influence zones

To account for the factors connected to the size of migration flows, we employed a negative binomial regression model with the number of international students for each pair of city and destination as the outcome, and a set of predictors, measuring location factors, offline and online metrics of cultural connections, institutional presence and religious affinity between the city and the region. The final set of best predictors selected after filtering out sources of multicollinearity appears in Table 1 with their descriptive statistics. Forward stepwise selection with AIC-based comparison was used to derive the model (Table 2).

3 ANALYSIS AND RESULTS

Patterns of outgoing educational migration. The chi-square test showed statistically significant differences ($\chi^2 = 24495$, $p < 0.001$) in the city-region contingency table. We highlight cities with significant positive deviations from the expected counts in Figure 1, showing dominant destination region patterns.

Cities located in the Russian Far East and East Siberia are in the sphere of China's influence. In Western Siberia and further to the west, the significance of China is smaller. Middle East (green) influence is visible in two zones: North Caucasian republics in the south and Tatarstan with Bashkortostan in the Volga Federal District (multiethnic regions with a high share of Muslim population). The north-west of Russia is in the Nordic (blue) sphere of influence. These territories have a long history of successful cultural and economical relations.

Significant outliers violate overall pattern. For example, Elista – a city in the south of Russia – is far away from China, but still sends many students there. The city is one of the centres of Buddhism in Russia. Kizil – the capital city of Tuva republic in East Siberia – has a dominant mobility flow to China. However, there is significant migration to the Middle East, despite the large distance and lack of apparent institutional connections according to state survey data: less than 1% of the Muslim population. Social media metrics show that the Muslim community in the predominantly Buddhist Tuva republic is very active. Local Muslim public groups in VK are larger and more active than the Buddhist's ones (major religion in the city).

To take into account these factors, we further explored factors influencing educational migration with negative binomial regression (see Table 2). The model showed significant negative relation

Table 2: Negative Binomial Model Summary

Dependent var.: # of ed. migrants	IRR	
Mean dist. to dest. countries(log)	0.41***	$R^2 CS$ 0.793
Presence of dest. cultural institutions	2.32***	$R^2 N$ 0.794
# ed. migrants from city(log)	2.23***	D 16.705
% of city pop. self-assoc. with main dest. religion	1.01***	$\chi^2 dev.$ 0.000***
# "dest.-country" VK groups per mil	8.71***	N.Obs. 489
Dist. to nearest 1mln city in Russia (100km)	1.02***	LL -1,401.251
Constant	77.04***	AIC 2,816.502

Note: *** $p < 0.01$

between the logarithm of average geographical distance from the origin city to the destination countries in agreement with gravity model of migration.

Proxies for institutional and cultural connections, in particular, the existence of respective cultural centres as well as racial and religious similarity between the sending city population and the destination countries are associated with higher migration rates. Social media metrics of international connections (number and size of country-related public groups on VK) is a significant predictor of migration.

Another factor is an "alternative pull" – proximity to a city with a population over 1 million. The further the city from large metropolitan areas with well-developed tertiary education, the more students it sends abroad.

4 CONCLUSION

The most important result of our study is the evidence of significant regional differences of migration patterns within the sending country, in our case, Russia. Stretching for thousands of miles between Europe and the Pacific Ocean, Russia is a model case to study gravity effects in educational migration. Besides gravitational pull, there are significant effects of cultural affinity between the sending area and the destination country. Our study provides a new dimension to the analysis of transnational and cross-border education by showing that the sending country is divided into "spheres of educational influence". It shows that Web-based data can provide researchers with new insights into international education.

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REFERENCES

- [1] Daniel Alexandrov, Viktor Karepin, and Ilya Musabirov. 2016. Educational Migration from Russia to China: Social Network Data. In *WebSci '16*. ACM, 309–311. <https://doi.org/10.1145/2908131.2908192>
- [2] George A. Barnett, Moosung Lee, Ke Jiang, and Han Woo Park. 2016. The flow of international students from a macro perspective: a network analysis. *Compare: A Journal of Comparative and International Education* 46, 4 (2016), 533–559.
- [3] Michel Beine, Romain Noël, and Lionel Ragot. 2014. Determinants of the international mobility of students. *Economics of Education review* 41 (2014), 40–54.
- [4] C. Hughes, E. Zagheni, G. J. Abel, A. Wisniewski, A. Sorichetta, I. Weber, and A. J. Tatem. 2016. Inferring migrations: Traditional methods and new approaches based on mobile phone, social media, and other big data. *Brussels: European Commission* (2016).
- [5] Ingmar Weber. 2017. Digital Demography. In *Proceedings of the 26th International Conference on World Wide Web Companion*. International World Wide Web Conferences Steering Committee, 935–939.