The Long-Run Effects of R&D Place-based Policies: Evidence from Russian Science Cities

Helena Schweiger[1] Alexander Stepanov[1] Paolo Zacchia[2]

[1]EBRD

[2]IMT Lucca

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Motivation

- Innovation is a key driver of economic growth
- Innovation tends to be spatially clustered (spillovers)
- If innovation is an externality, what role for the government?
  - Either indirect (incentives) or direct (investment)
  - Both approaches can be **place-based**. A classical example is the Silicon Valley, tracing roots in U.S. military investment
  - Their effect is difficult to evaluate
- In emerging economies like **Russia**, a debate of particular relevance:
  - Innovation is essential to diversify the economy
  - Russia possesses excellent human capital resources as well as a tradition of localized R&D policies: **Science Cities**

Research question

Question

Do innovation-focused place-based policies have any **long-run** impact on local development? What is their effect on innovation and productivity, both at the municipal and firm level?

Contribution

1. First paper to evaluate the legacy of "innovation enclaves" in the former Soviet Union on innovation in present-day Russia
2. We assess the impact of Science Cities both at the municipal and at the firm level, employing two unique datasets
3. Municipal level data: a combination of geographical, historical and present characteristics of Russian municipalities
4. Firm-level data from BEEPS V: new and accurate measures of product and process innovation

Preview of the results

Methodology

- Municipal-level analysis: we **match** Science Cities to other historically similar localities
- Firm-level analysis: we estimate the effects of Science Cities on firms by specifying **distance decay** models

Main results

1. Science Cities still host a more educated population, a more developed, innovative and productive R&D sector, and more productive SMEs than matched municipalities
   - Long-run shift of the spatial equilibrium due to the policy
   - Mechanism: interaction of persistence & agglomeration forces
2. Some evidence that firms closer to Science Cities are more likely to engage in R&D and are more productive

Related literature (general)

1. (Localized) knowledge spillovers:
   - Jaffe et al. (1993), Moretti (2004), Bloom, Schankerman and Van Reenen (2013), Lychagin et al. (2016)
2. Evaluation of place-based policies:
   - Short-run: Neumark and Kolko (2010), Ham et al. (2011), Albouy (2012), Busso et al. (2013), Wang (2013)
   - Long-run: Kline and Moretti (2014), von Ehrlich and Seidel (2016)
3. Knowledge-focused place-based policies:
   - Felsenstein (1994), Westhead (1997), Siegel et al. (2003), Yang et al. (2009), Falck et al. (2010)
4. Military and R&D:
   - Moretti, Steinwander and Van Reenen (2016)

Related literature (Russia)

1. Mikhailova (2012)
   - Negative welfare effects from the regional demographic policies enacted by the Soviet Union
2. Ivanov (2016)
   - Russian regions with more R&D personnel before the transition do better today at expanding employment in more high-tech sectors
3. Cheremukhin, Golosov, Guriev and Tsyvinsky (2017)
   - The “Big Push” industrialization policy enacted in the Soviet Union under Stalin was effective, however its welfare cost was large and perhaps it did not succeed in shifting Russia onto a faster path of economic development
4. Andrienko and Guriev (2004)
   - Evidence of low rates of interregional mobility in Russia

Innovation system in the Soviet Union

- Best resources were allocated to sectors considered vital for national security, military (2/3 of R&D spending)
- Model: special-regime enclaves aimed at fostering innovation
- After WW2: **Science Cities** – middle-sized urban centers (95 in total) with a high concentration of R&D facilities
- High-skilled workers and researchers were relocated to Science Cities as part of the program
- Main research areas, in order of relevance:
  - Aviation, rocket and space science
  - Nuclear physics
  - Electronics, mechanics
  - Chemistry and chemical physics
  - Biology and biochemistry

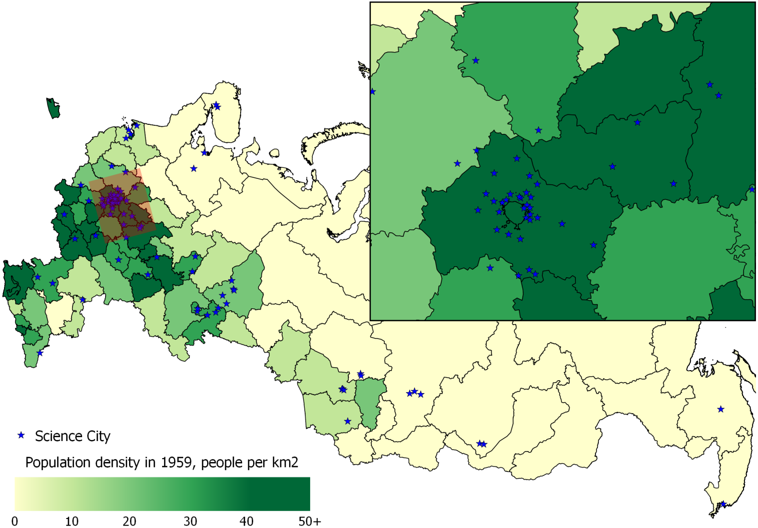
Science Cities: Characteristics

- Sources: Aguirrechu (2009), Kondratyeva and Sokolov (2009)
- About 2/3 of Science Cities were repurposed existing cities or settlements, others built from scratch in low-populated areas
- Benefited from generous investment – but difficult to quantify
- Urban layout and residential areas planned according to the best "rationalistic" criteria of the time (*resort towns*) Sarov
- Aim: to provide R&D workers and scientists with the best working conditions
- Some Science Cities were ZATOs: *closed cities* with restricted access, often appearing only on classified maps
  - However, not all ZATOs were Science Cities

Science Cities: Selection criteria

- Generally set in more socio-economically advanced areas of Soviet Russia, but selection criteria were quite diverse:
  - Isolated/remote areas were preferred for basic science activity and cities devoted to highly secretive projects (esp. ZATOs)
  - Locations with good transportation links were preferred for more applied R&D (for input-output connections)
  - Access to major water sources was necessary for some types of R&D activities (e.g. nuclear)
  - *Academic towns*: in Siberia, to foster local development
  - Many idiosyncratic factors at play (e.g. Sarov-Snezhinsk)
- Often, the potential for safety from outside interference (in the form of espionage, bombing) was the marginal factor in determining a Science City's location (Aguirrechu, 2009)

Science Cities: Location



Russian R&D and Science Cities after 1989

- The collapse of the Soviet Union brought about the collapse of its R&D sector as well
- Cumulated fall in R&D spending over GDP: >75% (and GDP shrank by >50%) Pic
- No. of researchers fell by >50%: as salaries were cut, many emigrated or changed their jobs Pic
- As the state went bankrupt, the Science Cities program was effectively discontinued
- Only recently has the government resumed the *Naukogrady* program, albeit restricted to 14 "official" cities only

A tale of two cities

Model details

- The enactment and later discontinuation of the Science City program bears some characteristics of a natural experiment
- A model can be useful to rationalize the findings about the long-run effects in terms of mechanisms
- Spatial equilibrium model adapted from Moretti (2011, 2014), itself built upon Rosen (1978), Roback (1979), Glaeser and Gottlieb (2008, 2009)
- Two cities: Science City s and an ordinary locality z
- Period 0 (USSR): labor is exogenously allocated by a planner, possibly inefficiently: **skilled** labor (h_{s0}, h_{z0}) with $h_{s0} > h_{z0}$; **unskilled** labor (ℓ_{s0}, ℓ_{z0}) with $\ell_{s0} \leq \ell_{z0}$
- Period 1 (capitalistic Russia): spatial equilibrium concept

Equilibrium predictions: High-skilled workers Details

- Employment log-ratio $(h_s - h_z)$:
  - Agglomeration forces alone are not sufficient to cause employment differentials; they only complement the inherent productivity differentials, superior amenities in Science Cities and persistence forces
- Productivity, wages log-ratio $((y_{hs} - y_{hz}) - (h_s - h_z) = (w_{hs} - w_{hz}))$:
  - If there are no agglomeration forces, difference is proportional to the log productivity differentials
  - If log productivity differentials are zero, any positive difference in the productivity and wages of high skilled workers between Science Cities and comparable locations is indicative of increasing returns

Equilibrium predictions: Low-skilled workers

Details

- Employment log-ratio $(\ell_s - \ell_z)$:
  - Sign is undetermined - amenities and spillovers from the high skilled may be counterbalanced by persistence forces
- Productivity, wages log-ratio $((y_{\ell s} - y_{\ell z}) - (\ell_s - \ell_z) = (w_{\ell s} - w_{\ell z}))$:
  - Any difference in sectors unrelated to R&D is evidence favorable to the operation of "generalized" spillover effects

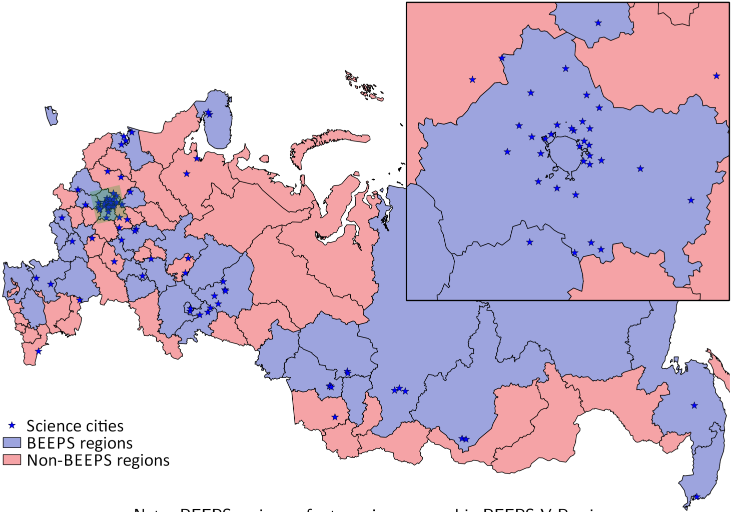
Three unique, interconnected datasets

1. List of Science Cities (with detailed information): based on Aguirrechu (2009), Lappo and Polyan (2008), NAS (2002) and publicly available information

2. Firm-level data at the plant level from the BEEPS V survey, including the novel innovation module:
   - 37 Russian regions, 4220 face-to-face interviews conducted between August 2011 and October 2012
   - Additional information allows more accurate measurement of product and process innovation
   - Matched to accounting data from BVD Orbis via a common unique ID present in BEEPS Descriptive statistics

3. Data on Russian municipalities (*rayon* level)

Science Cities and BEEPS



Note: BEEPS regions refer to regions covered in BEEPS V Russia.

Municipal-level database: Controls

Descriptive statistics

- **Geographical** data: coastline; major lakes & rivers; railroads in 1943; (coded as dummies or distances from *rayon* centroid)
- Also: average monthly **temperatures** 1960-1990; *rayon* **area**
- Population from the first post-WW2 **USSR Census** (**1959**)
- Data on factories, research and design **establishments** of the Soviet defense industry from Dexter and Rodionov (2016)
- No. of **higher education** institutions in 1959 from De Witt (1961); no. of **R&D** institutes in 1959 from various sources
- No. of branches of the **USSR State Bank** (proxy of a city's importance for planning, economic activity)

Municipal-level database: Outcomes

Descriptive statistics

- Population; pop. share with graduate education; pop. share with postgraduate (PhD/doctoral) degrees from the **2010 Russian Census**
- **Nighttime lights** from NOAA, 1992-1994 and 2009-2011
- Patent data from EPO **geolocated patents**, 2006-2015
- **Employment** and **salaries** in the **R&D** and **ICT** services from ROSSTAT (no full coverage, ZATOs excluded)
- 2010 Russian **small and medium enterprises** census data by industry (no full coverage, ZATOs excluded)
- Information on **municipal budgets** from ROSSTAT (no full coverage, ZATOs excluded)

Municipal-level methodology

- We match Science Cities s to other municipalities z that were similar to them when they were established: we pair neighbors in terms of the *Mahalanobis distance*:

$$m_{sz}\left(\mathrm{x}_s, \mathrm{x}_z\right) = \left(\mathrm{x}_s - \mathrm{x}_z\right)^{\mathrm{T}} \Sigma \left(\mathrm{x}_s - \mathrm{x}_z\right)$$

  where x_c is a vector of geographical/historical characteristics

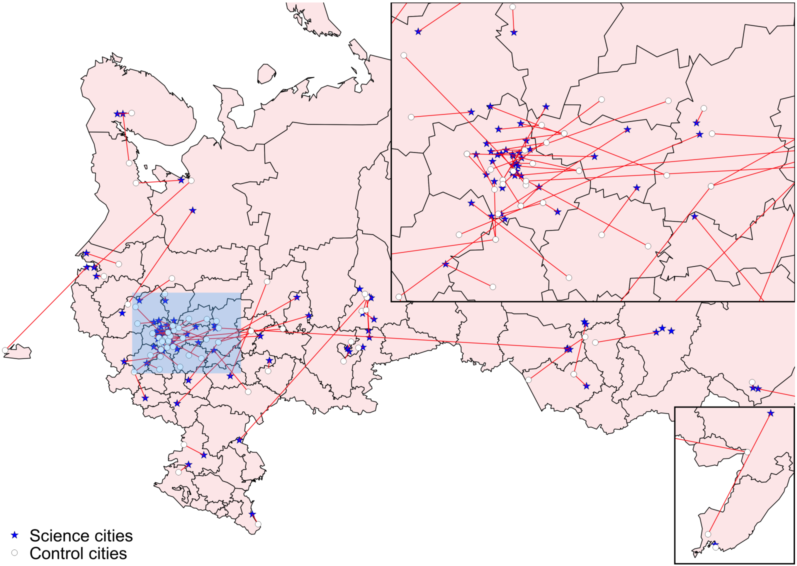
- We force **exact matching** on some dummy variables
- x_c also includes coordinates (looks for matches close in space)
- Identifying assumption: CIA; motivated by the peculiar selection criteria of Science Cities
- We replicate the analysis excluding current official *Naukogrady*
- Results are similar with Propensity Score Matching

Matching municipalities: Covariate balance

	Stand. bias		Variance ratio	
	Raw	Matched	Raw	Matched
Latitude	0.3592	0.0292	0.5429	0.9218
Longitude	-0.4503	0.0027	0.5346	0.9671
January mean °C	0.3916	0.0154	0.2750	1.0869
July mean °C	-0.0854	0.0418	0.4189	1.0892
Average altitude	-0.4050	-0.0214	0.0858	0.9828
(Log) population in 1959	-0.1273	-0.0006	2.1616	0.9714
(Log) area in km^2	-1.1775	-0.0581	1.1944	0.8159
(Log) no. of plants in 1947	0.7642	0.0683	2.3061	0.9678
(Log) no. of universities in 1959	0.3227	0.0058	3.1266	1.1697
(Log) no. of R&D institutes in 1959	0.7263	0.0523	4.8844	1.1064
Number of State Bank branches	-0.3294	-0.0633	1.0101	1.1924
Dist. from railroad	-0.4304	-0.0954	0.0015	0.8418
Dist. from USSR border	-0.0359	-0.0483	0.7059	1.0157
Dist. from coastline	-0.0537	-0.0172	1.3513	0.9962

- In addition, forcing exact matching on: ZATO status, presence of lake/river in the *rayon* territory, coastal city status
- For variables x with zero values, (Log) is meant as $\log(x+1)$
- Example: Science City Obninsk vs. non-Science City Skopin

Matching municipalities: Map



Municipal-level results: All Science Cities

	Whole sample	*Matched sample* (1 nearest neighbor)				
Outcome	Raw difference	T	C	ATT	ATT b.a.	Γ^*
Population	73.233*** (21.861)	83	65	23.435* (13.423)	24.324* (12.426)	3.55
Graduate share	0.115*** (0.008)	83	65	0.058*** (0.009)	0.053*** (0.009)	3.40
Postgraduate share	0.003*** (0.000)	83	65	0.003*** (0.001)	0.002*** (0.001)	2.80
Night lights (2009-2011)	22.973*** (2.130)	83	65	7.812*** (1.983)	6.824*** (1.853)	3.15
Fractional patents	11.644*** (3.676)	83	65	10.715*** (3.250)	10.999*** (3.245)	3.80
Avg. fractional patents	0.733** (0.312)	83	65	0.713** (0.332)	0.704** (0.333)	3.75
Employment in R&D, ICT	3.256*** (0.849)	63	54	2.312*** (0.474)	2.293*** (0.505)	3.25
Avg. salary in R&D, ICT	8.897*** (1.176)	63	54	8.181*** (1.563)	7.631*** (1.524)	2.75
No. SMEs, thousands (all)	2.050*** (0.741)	63	54	0.353 (0.460)	0.593 (0.582)	1.25
No. SMEs, thousands (manuf.)	0.276*** (0.103)	63	54	0.072 (0.077)	0.084 (0.090)	1.10
SME labor product. (all)	0.850*** (0.084)	63	54	0.416*** (0.084)	0.375*** (0.082)	2.55
SME labor product. (manuf.)	0.671*** (0.086)	63	54	0.323*** (0.094)	0.317*** (0.092)	1.65

Municipal-level results: Municipal budget outcomes

	Whole sample	Matched sample (1 nearest neighbor)				
Outcome	Raw difference	*T*	*C*	ATT	ATT b.a.	Γ^*
All Science Cities						
Total revenues, per capita	-5.714*** (1.335)	63	54	1.817* (1.042)	1.073 (0.994)	1.10
All transfers, per capita	-8.939*** (0.848)	63	54	-0.647 (0.646)	-1.103* (0.645)	1.00
Tax income, per capita	3.225*** (0.697)	63	54	2.464*** (0.618)	2.175*** (0.568)	2.00
Total expenditures, per capita	-5.594*** (1.319)	63	54	1.889* (1.060)	1.114 (1.015)	1.10
Expend. in education, per capita	2.950 (2.994)	50	45	6.719** (3.056)	4.915 (3.003)	1.25
Historical Science Cities						
Total revenues, per capita	-6.127*** (1.342)	50	45	0.023 (1.030)	-0.312 (1.132)	1.00
All transfers, per capita	-8.901*** (0.888)	50	45	-1.265* (0.670)	-1.630** (0.709)	1.05
Tax income, per capita	2.774*** (0.713)	50	45	1.289** (0.603)	1.318** (0.633)	1.30
Total expenditures, per capita	-6.004*** (1.326)	50	45	0.103 (1.062)	-0.245 (1.162)	1.00
Expend. in education, per capita	2.950 (2.994)	50	45	1.238 (2.929)	0.762 (3.361)	1.00

Firm-level methodology

- Firm innovation outcomes I_{fr} - probit models:

$$I^*_{fr} = \beta_0 + \sum_{\ell=1}^{L} \beta_\ell W_{fr,\ell} + \gamma \sum_{s=1}^{S} \exp\left[-\mathrm{dist}\left(f,s\right)\right] H_s + \eta_r + \varepsilon_{fr}$$

- Firm performance outcomes P_{fr} - OLS models:

$$\log P_{fr} = \tilde{\beta}_0 + \sum_{\ell=1}^{L} \tilde{\beta}_\ell W_{fr,\ell} + \tilde{\gamma} \sum_{s=1}^{S} \exp\left[-\mathrm{dist}\left(f,s\right)\right] H_s + \tilde{\eta}_r + \upsilon_{fr}$$

- H_s: Science Cities' patents, graduate or postgraduate share
- Main coefficients of interest: γ and $\tilde{\gamma}$, **distance decay** effects of distance between firm f and Science City s
- $(W_{fr,1}, \ldots, W_{fr,L})$: controls; η_r and $\tilde{\eta}_r$: region r fixed effects
- We do not address endogenous location

Firm-level innovation outcomes, probit average marginal effects ($\lambda = 1$)

Agglomeration potential measure	R&D	Product innovation	Process innovation	Technological innovation	Has a patent
Fractional patents	0.015***	0.012**	0.005	0.023	0.018***
	(0.003)	(0.005)	(0.009)	(0.016)	(0.006)
Graduate share	0.756	0.698	-0.529	0.519	0.931
	(0.493)	(0.528)	(0.720)	(0.783)	(0.642)
Postgraduate share	13.499	12.200	-10.478	9.368	18.536
	(18.595)	(15.758)	(22.860)	(24.771)	(21.692)
Fractional patents	0.018**	0.011	0.025	0.030	0.024
	(0.007)	(0.009)	(0.017)	(0.020)	(0.015)
Graduate share	-0.215	0.963	-7.043*	-2.354	-1.216
	(1.659)	(2.149)	(3.784)	(3.270)	(2.862)
Postgraduate share	-11.507	-35.355	143.479*	32.815	16.247
	(46.695)	(52.332)	(86.155)	(79.706)	(63.918)
Number of observations	4040	4040	4040	4040	1863
Number of strata	1224	1224	1224	1224	896

Notes: Average marginal effects based on probit using survey-weighted observations (using Stata's svy prefix). Only coefficients on agglomeration potential measures are reported. Fractional patents agglomeration potential measure is based on the number of patents applications to EPO in 2006-2015 in municipalities with science cities, by inventor (fractional counting). Graduate share and postgraduate education agglomeration potential measures are based on the percentage of population with higher education and postgraduate education, respectively, in municipalities with science cities in 2010. All regressions include region and sector fixed effects and control for other firm characteristics. Linearized Taylor standard errors clustered on strata are reported in parenthesis. * significant at 10%; ** significant at 5%; *** significant at 1%.

Firm-level performance outcomes, OLS ($\lambda = 1$)

Agglomeration potential measure	Operating revenue (Orbis)	Labor productivity (Orbis)	Sales (BEEPS)	Labor productivity (BEEPS)
Fractional patents	0.009	0.008	0.062**	0.056**
	(0.013)	(0.013)	(0.030)	(0.026)
Graduate share	3.233*	3.267*	0.722	-0.050
	(1.736)	(1.764)	(3.760)	(3.077)
Postgraduate share	101.608**	103.101**	-12.015	-31.789
	(51.006)	(51.345)	(111.069)	(92.718)
Fractional patents	-0.009	-0.009	0.092***	0.093***
	(0.011)	(0.014)	(0.029)	(0.030)
Graduate share	0.414	0.312	-3.007	-4.264
	(3.533)	(3.556)	(7.020)	(7.001)
Postgraduate share	97.645	102.369	-41.167	-27.543
	(127.543)	(127.531)	(190.713)	(191.855)
Number of observations	2809	2809	2926	2926
Number of strata	1086	1086	1074	1074

Notes: Simple OLS using survey-weighted observations (using Stata's svy prefix). Only coefficients on agglomeration potential measures are reported. Fractional patents agglomeration potential measure is based on the number of patents applications to EPO in 2006-2015 in municipalities with science cities, by inventor (fractional counting). Graduate share and postgraduate education agglomeration potential measures are based on the percentage of population with higher education and postgraduate education, respectively, in municipalities with science cities in 2010. All regressions include region and sector fixed effects and control for other firm characteristics. Linearized Taylor standard errors clustered on strata are reported in parenthesis. * significant at 10%; ** significant at 5%; *** significant at 1%.

Empirical results: Summary

- With respect to historically similar localities, Soviet-era Science Cities still host a larger and more educated population
- Science Cities are more innovative: *ceteris paribus* they produce more patents, employ more people in R&D and ICT services, and pay better salaries in those sectors
- Science Cities also do better in terms of some of our proxies of economic development: night lights and SME productivity
- The results for non-patent outcomes are unchanged when we remove the current official *Naukogrady* from the analysis
- There is some evidence that locating closer to a Science City positively affects firm R&D, sales and labor productivity

Mechanisms and interpretation

- Given our analysis of municipal budgets we rule out (a) federal transfers, and (b) persistent spending (as in Ehrlich and Seidel) as drivers of the results, which we interpret as long-run effects
- These are consistent with a permanent (no reversion) long-run shift of the spatial equilibrium:
  - The place-based policy has shifted local employment (high-skilled R&D workers)
  - However, because of non-linear agglomeration forces (knowledge spillovers), this impacted local productivity
  - Thus, even after transition to a market economy, many researchers and engineers stayed in the area due to better opportunities, but possibly changed their jobs/employer
  - There is no rebound to a pre-intervention spatial equilibrium
- Persistence of local human capital may also be explained by other factors (frictions to interregional mobility)

Thank you for your attention!

schweigh@ebrd.com

stepanoa@ebrd.com

paolo.zacchia@imtlucca.it

Primitives: Preferences

Individual i's log-utility $(n = h, \ell;\ c = s, z)$:

$$u_{nic} = w_{nc} + a_c + e_{nic}$$

- w_{nc} is the nominal log-**wage**.
- a_c are the **amenities**: a place's likable (or unlikable) features, with $\tilde{a} \equiv a_s - a_z \geq 0$ (Science Cities are better).
- e_{nic} is i's **idiosyncratic preference** for city c, with:

  $$e_{nis} - e_{niz} \sim \mathcal{U}\left[b_n - m_n, b_n + m_n\right]$$

  in our baseline case, $b_h = b_\ell = 0$ (as in Moretti's).
- We exclude negative congestion effects (rents) for simplicity.

Primitives: Technology

- Different firms employ different (h, ℓ) workers. A simplifying assumption in Moretti, arguably more realistic in this context.

- Log production functions in city $c = s, z$:

$$y_{hc} = x_{hc} + \theta_h h_c + \mu h_c + (1 - \mu)\, k_{hc}$$
$$y_{\ell c} = x_{\ell c} + \theta_\ell h_c + \mu \ell_c + (1 - \mu)\, k_{\ell c}$$

  where x_{nc} is a stochastic shock; $\tilde{x}_c \equiv x_{hc} - x_{\ell c}$.

- $\theta_h \geq 0$ measures **agglomeration economies** or **knowledge spillovers** between high-skilled workers.

- $\theta_\ell \geq 0$ measures **general spillovers** flowing from high-skilled to low-skilled workers (h_c is given for type-ℓ firms).

- Capital k_{nc} is (nationally) infinitely supplied at a fixed price.

Spatial equilibrium

Back

- In period 1 (fall of the USSR) workers are allowed to move
- We allow persistent barriers to mobility, or any asymmetrical preferences for workers already established in one city, as:

$$b_h = b\left(h_{s0} - h_{z0}\right) > 0$$
$$b_\ell = b\left(\ell_{z0} - \ell_{s0}\right) \leq 0$$

  where $b\left(\cdot\right)$ is increasing monotone with $b\left(0\right) = 0$

- If Science Cities have more h workers in $t = 0$, the marginal h worker is now less inclined to move to z; symmetrically for ℓ
- The spatial equilibrium concept is as in Moretti: the marginal worker of either type must be indifferent between s, z
- Generally no full worker segregation by skill if $m_h, m_\ell > 0$

Equilibrium predictions: high-skilled workers

Back

- Employment log-ratio:

$$(h_s - h_z) = \frac{\left[\tilde{x}_h + \mu\left(\tilde{a} + b_h\right)\right]\overline{h}}{\mu m_h - \theta_h \overline{h}} \geq 0$$

Agglomeration forces: $\theta_h > 0$ cannot drive type h employment alone, but can reinforce labor supply determinants: differential amenities $\tilde{a}$ and persistence forces b_h.

- Productivity, wages log-ratio:

$$(y_{hs} - y_{hz}) - (h_s - h_z) = (w_{hs} - w_{hz}) = \frac{m_h \tilde{x}_h + \theta_h \overline{h}\left(\tilde{a} + b_h\right)}{\mu m_h - \theta_h \overline{h}}$$

If $\mathbb{E}\left[\tilde{x}_h\right] = 0$ (arguably so in our empirical analysis) it can only be positive, on average, if $\theta_h > 0$

Equilibrium predictions: low-skilled workers

Back

- Employment log-ratio:

$$(\ell_s - \ell_z) = \frac{\bar{\ell}}{m_\ell}\left[\frac{\tilde{x}_\ell + \theta_\ell (h_s - h_z)}{\mu} + \tilde{a} + b_\ell\right] \gtrless 0$$

Its sign is undetermined: amenities $\tilde{a} \geq 0$ and spillovers from the high skilled $\theta_\ell (h_s - h_z) \geq 0$ may be counterbalanced by persistence forces $b_\ell \leq 0$

- Productivity, wages log-ratio:

$$(y_{\ell s} - y_{\ell z}) - (\ell_s - \ell_z) = (w_{\ell s} - w_{\ell z}) = \frac{\tilde{x}_\ell + \theta_\ell (h_s - h_z)}{\mu}$$

If $\mathbb{E}[\tilde{x}_h] = 0$ (arguably so in our empirical analysis) it can only be positive, on average, if $\theta_l > 0$ and $(h_s - h_z) > 0$

Descriptive statistics: Firm-level variables

Back

	Obs	Mean	Linearized std. error	[95% Conf.	interval]
Young firms (0-5 years)	4220	0.169	0.054	0.063	0.274
25%+ foreign owned	4220	0.058	0.040	-0.020	0.136
25%+ state owned	4220	0.009	0.007	-0.005	0.022
Exporter	4220	0.209	0.056	0.098	0.320
Main market: local	4220	0.502	0.043	0.418	0.587
Main market: national	4220	0.495	0.043	0.410	0.579
% of employees with a completed university degree	4045	55.639	3.793	48.181	63.097
Located in a city with population over 1 million	4220	0.605	0.011	0.583	0.626
Credit-constrained firm	4220	0.412	0.060	0.294	0.529
Log (employees), Orbis	2979	3.910	0.062	3.789	4.032
Log (capital), Orbis	3027	6.169	0.219	5.738	6.599
Log (materials), Orbis	2936	6.601	0.238	6.132	7.069
Log (permanent, full-time employees), BEEPS	4211	3.528	0.167	3.200	3.856
Log (operating revenue), Orbis	2980	6.891	0.217	6.465	7.317
Log (labor productivity), Orbis	2979	2.956	0.168	2.626	3.286
Log (sales), BEEPS	3027	17.889	0.209	17.478	18.299
Log (labor productivity), BEEPS	3021	14.346	0.182	13.989	14.704
R&D (dummy)	4220	0.315	0.058	0.201	0.429
Technological innovation (dummy)	4220	0.471	0.058	0.356	0.586
Product innovation (dummy)	4220	0.326	0.058	0.211	0.441
Process innovation (dummy)	4220	0.306	0.053	0.201	0.410
Ever granted a patent (dummy)	1998	0.163	0.053	0.059	0.267

Notes: Survey-weighted observations (using Stata's svy command). Linearized Taylor standard errors clustered on strata.

Descriptive statistics: Municipal controls

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	Science Cities Obs.	Mean (SE)	Other municipalities Obs.	Mean (SE)	*p*-value
Latitude	88	55.664	2250	53.981	0.000
		(0.391)		(0.108)	
Longitude	88	49.771	2250	59.955	0.000
		(2.387)		(0.620)	
January mean $^{\circ}$C	88	-11.632	2250	-13.559	0.000
		(0.410)		(0.149)	
July mean $^{\circ}$C	88	18.535	2250	18.755	0.247
		(0.181)		(0.056)	
Average altitude	88	0.169	2250	0.267	0.000
		(0.010)		(0.007)	
Minimum distance from railroad	88	0.007	2250	0.078	0.000
		(0.001)		(0.005)	
Minimum distance from river	88	0.032	2250	0.056	0.000
		(0.004)		(0.001)	
Minimum distance from lake	88	0.118	2250	0.172	0.000
		(0.009)		(0.003)	
Minimum distance from USSR border	88	0.665	2250	0.679	0.723
		(0.037)		(0.009)	
Population in 1959	88	67.583	2250	49.573	0.167
		(12.516)		(3.242)	
Number of universities in 1959	88	0.557	2250	0.196	0.132
		(0.224)		(0.046)	
Number of State Bank branches	88	1.096	2250	0.739	0.000
		(0.987)		(0.977)	
Number of plants in 1947	88	6.205	2250	2.484	0.023
		(1.458)		(0.697)	
Number of R&D institutes in 1959	88	0.807	2250	0.412	0.242
		(0.253)		(0.222)	
Area in km^2	88	0.692	2250	7.108	0.000
		(0.116)		(0.637)	

Descriptive statistics: Municipal outcomes

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	Science Cities		Other municipalities		
	Obs.	Mean (SE)	Obs.	Mean (SE)	*p*-value
Night lights, 2009-2011	88	30.611	2250	7.638	0.000
		(2.124)		(0.272)	
Population in 2010	88	131.557	2250	58.324	0.001
		(21.169)		(5.871)	
Graduate share in 2010	88	0.225	2250	0.110	0.000
		(0.008)		(0.001)	
Postgraduate share in 2010	88	0.006	2250	0.003	0.000
		(0.000)		(0.000)	
Fractional patents, 2006-2015	88	13.909	2250	2.265	0.002
		(3.489)		(1.210)	
Avg. fractional patents, 2006-2015	88	0.761	0.028	2.265	0.000
		(2.944)		(0.107)	
Salary in R&D and ICT (thousands)	73	24.265	2177	15.368	0.000
		(10.001)		(7.978)	
Employment in R&D and ICT (thousands)	73	4.260	2177	1.004	0.026
		(6.937)		(12.394)	
Employment per capita in R&D and ICT	73	0.038	2177	0.007	0.009
		(0.039)		(1.210)	
Number of SMEs in 2010 (thousands, all)	69	3239.725	2140	1189.833	0.008
		(742.669)		(67.367)	
Number of SMEs in 2010 (thousands, manuf.)	69	395.073	2038	119.546	0.010
		(103.133)		(7.535)	
SMEs per 1000 people (all)	69	0.025	2159	0.027	0.086
		(0.001)		(0.000)	
SMEs per 1000 people (manuf.)	69	0.002	2038	0.002	0.066
		(0.000)		(0.000)	
SME labor productivity (all)	69	1643.995	2153	794.105	0.000
		(84.513)		(9.213)	
SME labor productivity (manuf.)	67	1438.443	2014	768.462	0.000
		(84.554)		(20.805)	

Municipal-level results: No current *Naukogrady*

	Whole sample	*Matched sample* (1 nearest neighbor)				
Outcome	Raw difference	T	C	ATT	ATT b.a.	Γ^*
Population	82.854*** (25.398)	69	58	27.166* (14.277)	28.475** (13.879)	3.30
Graduate share	0.103*** (0.009)	69	58	0.042*** (0.009)	0.040*** (0.008)	2.75
Postgraduate share	0.003*** (0.000)	69	58	0.002*** (0.000)	0.002*** (0.000)	2.20
Night lights (2009-2011)	20.101*** (2.318)	69	58	5.959** (2.066)	5.615*** (1.907)	2.45
Fractional patents	7.254*** (2.703)	69	58	5.448*** (1.353)	5.860*** (1.285)	2.85
Avg. fractional patents	0.253*** (0.058)	69	58	0.195*** (0.065)	0.182*** (0.065)	2.70
Employment in R&D, ICT	3.256*** (0.849)	50	45	1.702*** (0.442)	1.612*** (0.509)	2.25
Avg. salary in R&D, ICT	8.481*** (1.361)	50	45	7.000*** (1.832)	6.835*** (1.762)	1.90
No. SMEs, thousands (all)	2.050*** (0.741)	50	45	0.196 (0.553)	0.348 (0.735)	1.05
No. SMEs, thousands (manuf.)	0.276*** (0.103)	50	45	0.052 (0.095)	0.059 (0.116)	1.00
SME labor product. (all)	0.850*** (0.084)	50	45	0.312*** (0.084)	0.304*** (0.082)	1.90
SME labor product. (manuf.)	0.671*** (0.086)	50	45	0.226*** (0.094)	0.247*** (0.094)	1.20

Municipal-level results: "Dynamic" outcomes

	Whole sample	*Matched sample* (1 nearest neighbor)				
Outcome	Raw difference	*T*	*C*	ATT	ATT b.a.	Γ^*
All Science Cities						
Graduate share: born $\leq$ 1965	0.125*** (0.010)	83	65	0.071*** (0.011)	0.064*** (0.010)	3.80
Graduate share: born $>$ 1965	0.109*** (0.007)	83	65	0.046*** (0.009)	0.040*** (0.009)	2.45
Postgraduate share: born $\leq$ 1955	0.004*** (0.001)	83	65	0.003*** (0.001)	0.003*** (0.001)	2.90
Postgraduate share: born $>$ 1955	0.003*** (0.000)	83	65	0.002*** (0.001)	0.002*** (0.001)	1.95
Night lights (1992-1994)	19.142*** (1.959)	83	65	5.603*** (1.677)	4.746*** (1.534)	1.80
Historical Science Cities						
Graduate share: born $\leq$ 1965	0.110*** (0.010)	69	58	0.049*** (0.010)	0.047*** (0.009)	3.05
Graduate share: born $>$ 1965	0.100*** (0.008)	69	58	0.033*** (0.009)	0.031*** (0.008)	1.95
Postgraduate share: born $\leq$ 1955	0.003*** (0.000)	69	58	0.002*** (0.001)	0.002*** (0.001)	2.30
Postgraduate share: born $>$ 1955	0.003*** (0.000)	69	58	0.002*** (0.001)	0.002*** (0.001)	1.55
Night lights (1992-1994)	16.768*** (2.129)	69	58	4.491*** (1.754)	3.954*** (1.566)	1.35

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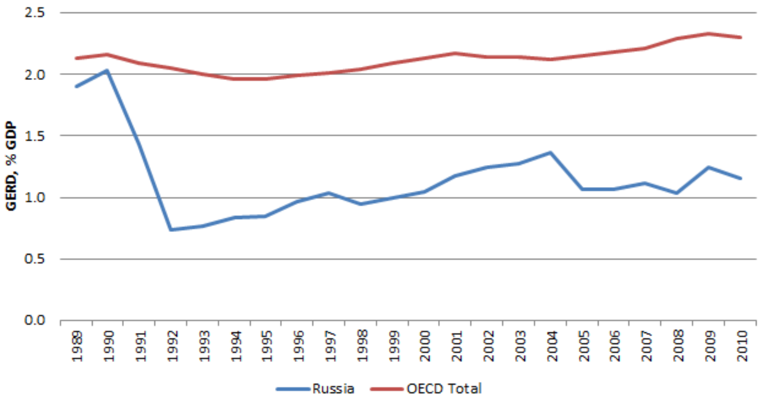
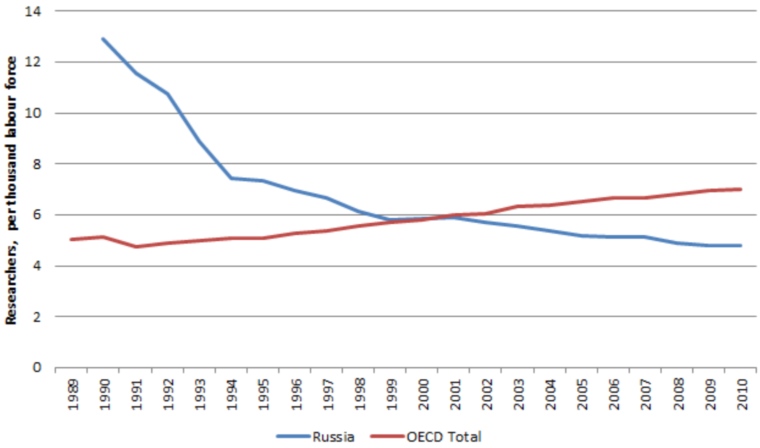
R&D spending over GDP in Russia after 1989 Back



Number of Russian researchers after 1989 Back



Obninsk vs. Skopin

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(a) Obninsk (Science City)

(b) Skopin (non-Science City)

- Obninsk (Kaluga region) is "the first Science City of Russia." It was founded in 1945 out of small local villages, as the first R&D institute was created. The world's first nuclear plant was opened there in 1954. It still hosts a number of R&D facilities as of today. Its population is 104,739 as per the 2010 Census.

- Skopin (Ryazan region) is one of the oldest settlements in Russia. While rich in coal and renowned for its ceramics, it never gained prominence. Its population is 30,376 as per the 2010 Census.

- Both cities lie close to the boundary with the larger Moscow region.