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

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Abstract

We study the long run effects of a unique historical place-based policies targeting R&D: the creation of "Science Cities" in former Soviet Russia. The establishment of Science Cities and the criteria for selecting their location were largely guided by political and military-strategic considerations. We compare current demographic and economic characteristics of Science Cities to those of appropriately matched localities that were similar to them at the time of their establishment. We find that in the modern Russian economy, despite the massive cuts of governmental support to R&D that followed the dissolution of the USSR, Science Cities host more high-skilled workers and more developed R&D and ICT sectors; are the origin of more international patents; and generally appear to be more productive and economically developed. Within a spatial equilibrium framework, we interpret these findings as the result of the interaction between persistence and agglomeration forces. Furthermore, we rule out alternative explanations that have to do with the differential use of public resources, and we find limited support for a case of equilibrium reversion. Finally, by analyzing firm-level data we obtain evidence in favor of spillover effects with a wide spatial breadth.

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1 Introduction

The effectiveness of public support to science and R&D is a longstanding issue in the economics of innovation. Both direct subsidies and indirect incentives to research and science are usually motivated on the existence of positive externalities (or other types of market failures) which, in the absence of public intervention, cause underinvestment in R&D. Some specific innovation policies, like the top-down creation of local R&D clusters, are characterized by a geographical *local* dimension. In such contexts, assessing the spatial extent of knowledge spillovers – one of the three forces of spatial agglomeration first identified by Marshall (1890), corresponding with the "learning" effect from the more recent classification by Duranton and Puga (2004) – is relevant for evaluating the overall effect of the intervention. Moreover, the debate about localized innovation policies mixes with the one about broader (that is, not innovation-specific) *place-based* policies. In particular, it is argued whether place-based policies have any long-run effect, in the absence of which their net welfare effect is as likely to be negative as much as positive (Glaeser and Gottlieb, 2008).[1]

This paper examines the long-run impact of a specific localized innovation policy: the establishment of highly specialized "Science Cities" in the territory of modern Russia during Soviet times. These are ninety-five middle-sized urban centers that were created or developed by the Soviet government according to a grand-strategic plan of technological advancement. Science Cities hosted a high concentration of R&D facilities – often the only driving economic activity in town – typically built around a specific technological purpose. Since Science Cities emerged in the context of technological and military competition of the Cold War, most of them were, unsurprisingly, specialized in military-applicable fields, such as nuclear physics, aerospace, ballistics and chemistry – although a minority of them were focused in other areas. The above sectors remain, to this day, those in which Russia maintains a comparative technological advantage.

[1] Their argument is based on the interaction between congestion effects and spatial agglomeration externalities – such as those due to local knowledge spillovers – in a spatial equilibrium model that allows for movement of workers across places. In their theoretical framework, place-based policies that move employment between areas are welfare-improving only if they are effective at shifting economic activity to a better long run equilibrium, one in which employment is reallocated in such a way that the increase in self-reinforcing agglomeration forces more than countervails the possibly negative effects from increased congestion. Multiple equilibria with such features are however only possible if agglomeration externalities feature non-linearities. This has motivated subsequent empirical research aimed at uncovering agglomeration effects and their (potential) non-linearities. See also the discussion by Glaeser and Gottlieb (2009) as well as that by Kline and Moretti (2014b).

While one may question whether the institutional context of Russian Science Cities is comparable to that of other industrialized countries, this historical experience stands out with some unique features that motivate its analysis. First, the locations of Science Cities were typically chosen by the Soviet leadership with criteria that are unusual for a capitalistic market economy. According to historical research on the topic (Aguirrechu, 2009), since the Soviet government had the power to allocate both physical and human capital where it deemed necessary, the potential for economic development and local human capital accumulation was typically not, *at the margin*, a determinant of a location's choice for the establishment of a Science City. Instead, between any two places that were similarly suited to host such a settlement, the choice usually fell over the one that offered better secrecy and safety from foreign interference (in the form of R&D espionage), or that satisfied other military and strategic criteria. This greatly diminishes concerns for selection biases due to unobserved determinants of future development, which typically affect studies about innovative clusters in other countries.

Second, the transition to a market economy that followed the dissolution of the USSR resulted in a large negative shock for Russian R&D, as direct governmental expenditure in R&D as a percentage of GDP fell by about 75%, causing half of the scientist and researchers of post-1991 Russia to lose their job. Consequently, state support for Science Cities was abruptly suspended; only recently it was partially resumed for fourteen of the former towns, which today bear the official name of *Naukogrady* ("Science Cities" in Russian). Together, these historical developments indicate that both the initiation and discontinuation of the Science Cities program were largely driven by exogenous factors, orthogonal to determinants of current demographic and economic conditions. In addition, by analyzing historical Science Cities separately from modern *Naukogrady*, we are able to evaluate to what extent the modern characteristics of the former depend on long run effects due to the Soviet-era policy, rather than on current governmental support.

We estimate the effect of the past establishment of a Science City on the following set of present characteristics of Russian municipalities: human capital (measured as the share of the population with either graduate or postgraduate qualifications), innovation (evaluated in terms of patent output) and various proxies of economic development. In order to give a causal interpretation to our estimates, we construct an appropriate control group by employing matching techniques. In particular, we match Science Cities to other localities that, at the time of selection, were similar to them in terms of characteristics that could affect both their probability of being chosen and their future outcomes.

Our main identifying assumption is that, conditional on these variables, the choice of a locality was determined at the margin by factors – such as *potential for secrecy* – that would be independent from future, post-transition outcomes. In order to implement this strategy we construct a unique dataset of Russian municipalities, which combines both historical and more recently observed local characteristics.

Our results can be summarized as follows. In today's Russia, Science Cities from the Soviet era still host a more educated population, are more economically developed, employ a larger number of workers in R&D and ICT-related jobs, and produce more patents than other localities that were comparable to them when the program started. Moreover, researchers working in former Science Cities appear to be more productive, and to receive substantially higher salaries. The estimated treatment effect is typically lower than the raw sample difference for all outcome variables except those related to patents, for which no ex-ante bias can be attested. When we exclude modern *Naukogrady* from the analysis our results remain largely unchanged, but the point estimates relative to total and per capita patent production decrease by about 60%. In addition, through a more in-depth analysis of our demographic outcomes and our night lights proxy for economic development we find little evidence for reversion towards a symmetric equilibrium.

We interpret our results in light of a spatial equilibrium model *à la* Glaeser and Gottlieb (2009) and Moretti (2011). In the model, the Soviet Union initially allocates workers of different skills in Science Cities and other localities; after the transition workers are allowed to move. The model provides different predictions about several city-level outcomes to the extent that Science Cities are inherently better places to live, workers' mobility is more or less restricted, the initial allocation modified individual preferences for location, or agglomeration forces such as knowledge spillovers exist. In light of these predictions, we interpret our empirical results about the productivity and wages of high-skilled workers as indicative of localized knowledge spillovers. This contrasts with the recent analysis by von Ehrlich and Seidel (2015) of West German municipalities situated along the Iron Curtain which used to be subsidized during the Cold War. Specifically, they attribute their finding of positive long-run effects not on agglomeration forces, but on the persistence of local infrastructural investment. Notably, we do not find evidence favorable to a similar mechanism in our examination of Russian municipal budgets.

We also complement our municipality-level empirical analysis with an additional set of estimates based on firm-level data. In particular, we employ data about Russian firms from the fifth round of the Business Environment and Enterprise Performance Survey

(BEEPS V), which were sampled from regions where the majority of Science Cities are located. Adopting a variety of specifications, we evaluate to what extent the distance of a firm from a Science City correlates with its outcomes about innovation and productivity. BEEPS V is particularly useful in this regard, as it features an innovation module with detailed information about recent innovative activities by firms. This analysis is meant to evaluate if, in the modern Russian economy, the effect of Science Cities spills over on other firms that are located nearby, and to what economic and geographical extent. The results reinforce our hypothesis that the the municipal-level differentials are at least in part caused by knowledge spillovers, since firms are observed to be more R&D-intensive, innovative and productive when locating relatively close to Science Cities.

Our paper contributes to various strands of the literature. First, we add to the set of studies about the evaluation of place-based policies; for a recent survey of the empirical research see Neumark and Simpson (2014). Most of these papers analyze policies enacted in the US (Neumark and Kolko, 2010; Busso et al., 2013; Kline and Moretti, 2014a) or in the EU (Bronzini and de Blasio, 2006; Criscuolo et al., 2012; Givord et al., 2013; von Ehrlich and Seidel, 2015). Among the few that focus, like us, on a non-western country, there is a notable contribution by Wang (2013) about Chinese Special Economic Zones (SEZs). The empirical challenges faced by these studies are typically about constructing appropriate control groups, and disentangling direct effects from spillovers. Methodologically, our paper is most directly related to the study by Kline and Moretti (2014a) on the Tennessee Valley Authority; like in their study, we apply a matching strategy in order to uncover the long run consequences of our policy of interest. Unlike Kline and Moretti, however, we find that these are not confined to the sector directly targeted by the policy, arguably because of the effect of knowledge spillovers.

Second, and relatedly, we contribute to the more general search of agglomeration effects – and in particular of the third Marshallian force, localized knowledge spillovers – in urban and regional economics. This has long been a traditional field of investigation for economic geographers, with a particular interest in innovation clusters. Following seminal contributions by Jaffe (1989), Glaeser et al. (1992), Audretsch and Feldman (1996) and others, a large literature has developed.[2] Recently, the issue has caught the attention of economists working in more diverse fields. Moretti (2004) shows that in US cities, the

[2]We propose two fairly recent surveys: Beaudry and Schiffauerova (2009) focus on the "Marshall vs. Jacobs" debate around the prevalence of, respectively, within- versus between-industry local knowledge spillovers; while Boschma and Frenken (2011) devote special attention to studies within the evolutionary economic geography research agenda.

level of education of the workforce affects firm productivity across sectors. Ellison et al. (2010) simultaneously test all three Marshallian theories by looking at the co-location of plants across industries. Greenstone et al. (2010) demonstrate the existence of local productivity spillovers following the opening of a “Million Dollar Plant.” In two separate contributions, Bloom et al. (2013) and Lychagin et al. (2016) find an association between firms’ R&D spending and the productivity of those nearby.[3]

The specific institutional setting of this paper relates it to other, somehow diverse contributions about the consequences of historically massive forms of government intervention on long-run economic and technological development, either in Russia or elsewhere. Cheremukhin et al. (2017) argue that the “Big Push” industrialization policy enacted in the USSR under Stalin did not succeed in shifting Russia onto a faster path of economic development. Mikhailova (2012) evaluates negative welfare effects from the regional demographic policies enacted by the Soviet Union. However, the picture looks different in the more specific case of R&D policies. Through an analysis performed at a higher level of geographic aggregation than ours, Ivanov (2016) finds that Russian regions with more R&D personnel before the transition do better today at expanding employment in high-tech sectors. Outside Russia, Moretti et al. (2016) show that in OECD countries increases in government-funded R&D for military purposes have positive net effects on TFP, despite crowding out private expenditures in R&D.

This paper is organized as follows. Section 2 briefly introduces the history and characteristics of Soviet Science Cities. Section 3 outlines the conceptual framework of the paper. Section 4 describes the data employed in both the municipal-level and firm-level analyses. Section 5 outlines our empirical methodologies. Sections 6 and 7 discuss the empirical results, respectively for the municipal-level and the firm-level analyses. Finally, Section 8 recapitulates and concludes the paper.

2 Historical and Institutional Background

This section is divided in two parts. In the first part, we summarize the historical experience of Science Cities from Soviet times to modern Russia. In the second part we focus in more detail on the selection criteria for the location of Science Cities.

[3]Other, related studies discuss to what extent patent citations can be exploited to recover patterns of localized knowledge spillovers. See e.g. the seminal contribution by (Jaffe et al., 1993), the critical revision of that original analysis by Thompson and Fox-Kean (2005), as well as the study by Breschi and Lissoni (2009) which controls for co-authorship networks.

2.1 History of Science Cities

The former Soviet Union was in a way a pioneer in public investment in science and in place-based policies that focused on R&D. In the context of the Cold War competition between the USA and the USSR, the Soviet leadership prioritized the allocation of the best resources – including human ones – to sectors considered vital to the country's national security. Around two-thirds of all Soviet R&D spending was set for military purposes, and almost all of the country's high-technology industry was in sectors directly or indirectly related to defense (Cooper, 2012). Science Cities emerged in this environment. They were 95 middle-sized urban centers which the Soviet government endowed with a high concentration of research and development facilities, and they were devoted to a particular scientific and technical specialization.[4] Science Cities began to develop around strategically important (military) research centers from the mid-1930s;[5] however, the majority of them were established after the Second World War, especially in the 1950s. See Table A.1 in the Data Appendix for more details about each Science City.

As they specialized in industries with high technological intensity, Science Cities needed access to suitable equipment, machinery, intermediate inputs and qualified personnel. With the objective of co-locating scientific research centers, training institutes and manufacturing facilities, the Soviet government established about two thirds of Science Cities by "repurposing" existing settlements, while the rest were built from scratch (Aguirrechu, 2009). For the sake of providing better incentives to individuals working in Science Cities, the Soviet government strove to provide in these localities better living conditions than the Soviet standard, by making available to residents a wider choice of retail goods, more comfortable apartments as well as more abundant cultural opportunities than elsewhere in the country. Typically, the urban characteristics of Science Cities were better than those of other contemporary settlements, as the former were developed according to the best urban planning criteria of the time (Aguirrechu, 2009).

Starting in the 1940s, with the need to protect the secrecy of the nuclear weapons program in the Cold War environment (Cooper, 2012), many Soviet municipalities of

[4]The term "Science City" (*Naukograd*) was first introduced in 1991 (Ruchnov and Zaitseva, 2011). The former Soviet Union was not a Science Cities pioneer — the first Science City was established in 1937 in Peenemünde, Germany — but it has implemented the idea to a much larger extent.

[5]The model of innovation followed by the Soviet authorities since the early 1930s was the creation of "special-regime enclaves intended to promote innovation" (Cooper, 2012). These enclaves first appeared as secret research and development laboratories (so-called Experimental Design Bureaus or *sharashki*) in the Soviet Gulag labor camp system. The scientists and engineers employed in a *sharashka* were prisoners picked from various camps and prisons, and assigned to work on scientific and technological problems.

military importance were “closed” to external access in order to maintain security and privacy: non-residents needed an explicit permission in order to to travel to closed cities and were subject to document checks and security checkpoints; relocating to a closed city required a security clearance by the KGB; foreigners were prohibited from entering them at all; and dwellers had to keep their place of residence secret. Science Cities whose main objective was to develop nuclear weapons, missile technology, aircraft and electronics were closed as well; some of them were located in remote areas situated deep in the Urals and Siberia – out of reach of enemy bombers – and were represented only on classified maps. Note that the two sets of “Science Cities” and “closed cities” overlap only partially, a fact that we take into account in our empirical analysis.

Following the dissolution of the USSR, Russia underwent a difficult transformation from a planned to a market economy. The withdrawal of the state from many sectors of the economy dramatically affected R&D as well. In Russia, gross R&D expenditures as a fraction of GDP fell from the 1990 level of about 2% to a mere 0.74% in 1992.[6] This is even more dramatic in face of the fact that the Russian GDP shrank by about 50% in the initial years of the transition. As a consequence of much lower wages, total employment in R&D also fell by about 50%.[7] This has inevitably affected Science Cities: while we lack access to detailed information about governmental funding to them in the 1990s, anecdotal evidence speaks of an effective discontinuation of the military research programs that Science Cities were responsible for, at least until the government, starting in the early 2000s, re-established direct support for the 14 modern *Naukogrady* mentioned in the introduction. Our analysis of municipal budgets of modern Russia (see Section 6), confirms that Science Cities receive today, if anything, *less* governmental transfers than comparable towns, especially if modern *Naukogrady* are removed from the count.

2.2 Location of Science Cities

Given the nature of the period during which most Science Cities were established and the associated political context, any systematic, reliable and transparent information on

[6] We calculated these figures using as sources: Gokhberg (1997), the Russian Statistical Yearbooks for various years, and the OECD Main Science and Technology Indicators (MSTI) database.

[7] Whereas in Soviet times the wages of scientists were 10-20% higher than average, they dropped to 65% of the average wage already in 1992 following the withdrawal of the state from the R&D sector (Saltykov, 1997). Even worse, during the 1990s many scientists did not even receive their salary, or received only a fraction of it (sometimes in kind) over extended periods (Ganguli, 2014). Low remuneration was not the only reason for researchers to leave the R&D sector: with the removal of previous restrictions to individual mobility, scientists were allowed to migrate abroad.

how their locations were chosen does not exist. Thanks to the cited historical research by Aguirrechu (2009), however, it is possible to identify some general factors that drove the choice of locations for specific groups of Science Cities. Two general themes emerge from our reading of Aguirrechu's work. First, the relevant natural, socio-economic and demographic factors that influenced the choice of a place usually varied by the specific function of a Science City. Second, *at the margin* the choice of a location over another usually depended on political, military and security motivations that are arguably unrelated with the determinants of economic outcomes in a typical market economy. These two considerations, on which we expand below, inform the empirical strategy of this paper. Specifically, our matching strategy rests on the assumption that controlling for certain relevant factors, Science City status is unrelated to current outcomes.

In terms of socio-economic and demographic characteristics that affected the location of Science Cities, the most relevant one that is identified by Aguirrechu is, unsurprisingly, the pre-existing level of economic and social development. Figure 1 depicts the location of Science Cities superimposed on the chloropleth map of Russian regions distinguished by population density. With some exceptions, Science Cities were established in the areas of Russia that were the most industrialized, urbanized, and with a better educated population, so that they could have easier access to qualified personnel or be able to attract it with minor additional costs. For this reason, arguably, Science Cities are also for the most part located in the western, warmer part of Russia, within the humid continental climatic region typified by large seasonal temperature differences. Historically, in fact, the socio-economic development differentials between Russian regions strongly correlates with temperature gradients along a longitudinal axis.[8]

Other geographical factors differ by type of Science City. Those engaging primarily in basic R&D were typically semi-isolated, to be found either in outer parts of a region or in the territories between major highways and railroads. Science Cities engaging primarily in applied, production-oriented R&D in civil- or double-purpose industries (such as electronics or aviation), by contrast, were located either close to the regional capital or in the proximity of transportation links: with a very Marshallian motivation, these cities were in more need of easy access to both upstream suppliers and downstream "buyers" (a term to be interpreted in the context of a socialist economy). Heavy industry and nuclear technology needed large amounts of water, therefore Science Cities specialized

[8]In Russia, temperature changes more along the west-east axis, than along the north-south axis; thus, for two localities with the same latitude, the eastern one is typically colder.

in those areas were typically built close to rivers or lakes. For analogous reasons, those Science Cities focused in military shipbuilding clearly had to be located on the coast.

The exact location of Science Cities, however, often depended on very idiosyncratic factors whose main motivation was military, political or strategic. In general, Aguirrechu underlines the fact that, whenever a Science City had to be set in an urbanized and relatively developed region, between any two similar localities the choice usually fell on that with the most potential to maintain secrecy and minimize the threat of spying; he supports this argument with anecdotal evidence. In this respect, it is not surprising that many Science Cities were established in the proximity of Moscow, close to the central government and the headquarters of security agencies such as the KGB. At the extreme, considerations of this kind overrode all the others. In particular, Science Cities specializing in some applied R&D fields such as the production of nuclear and strategic arms faced a much higher threat of bombing and spying; and were located in regions far from the borders and in municipalities far from the regional center (with limited transport links) and previously poorly populated. Examples include Sarov and Snezhinsk.[9]

Some of these idiosyncratic factors depended on other historical and political circumstances. Following the evacuation of factories from the European part of the Soviet Union beyond the Urals during the Second World War, those areas developed rapidly. On the one hand, this may explain the concentration of many Science Cities in the Urals area. On the other hand, this was a historical driver for the establishment of a particular class of Science Cities, the so-called "academic towns" (*akademgorodki*), in Siberian centers to the East of the Urals with rising industrial and strategic importance but limited scientific capacities. Academic towns were semi-isolated neighborhoods of a larger city, endowed with R&D facilities, housing for R&D staff and their families, as well as basic local infrastructure; the research in natural sciences that was conducted in academic towns was directly linked to the specific issues faced by Siberia (Aguirrechu, 2009).

[9]These two places provide a particularly indicative example of idiosyncratic factors affecting the location of Science Cities: sometimes, this was determined by the presence of other Science Cities, or lack thereof. Specifically, Snezhinsk (located in the Chelyabinsk region) was established as a double of Sarov (in the Nizhny Novgorod region) with the main purpose of keeping the industry working even if one of the two places were destroyed, but also to create inter-City competition. Since Sarov is located in a relatively remote location in the European part of Russia, Snezhinsk hat to be placed in a similarly out-of-reach area, but to the East of Urals. Officials reportedly considered other locations in different regions, but ultimately decided on Snezhinsk because of its proximity to another Science City, Ozyorsk, which could supply inputs to Snezhinsk. A similar pattern of interplay between decisions affecting different Science Cities was not unique; for example, the four places specialized in the production of enriched uranium were also located far from each other.

3 Analytical Framework

We interpret the long-run effect of the establishment of Science Cities in light of a spatial equilibrium framework typical of the Urban Economics literature. Specifically, we adapt the model by Moretti (2011, 2013) which itself extends Rosen (1979), Roback (1982) and Glaeser and Gottlieb (2008, 2009). This adaptation is designed to correspond with our empirical strategy: in the model, we describe two ex-ante identical cities, one of which became a Science Cities, and we analyze the spatial equilibrium that would emerge in a market economy. We focus our discussion on the economic mechanisms that could endogenously explain the post-transition differences between the two cities for selected outcomes of interest. In what follows, we sequentially describe the setup of the model and the post-transition spatial equilibrium.

3.1 Model Setup

Consider two ex-ante identical cities, s and z, which could be inhabited by different types of workers: those of high educational level or "skill," and those of relatively lower skill. This dichotomous classification is typically interpreted in terms of differences in higher educational achievement. In this context, high-skilled workers can be more narrowly identified as researchers engaged in R&D, with low-skilled workers residually representing all other individuals (including university-educated) who are employable in all other sectors. The model is general enough to allow for both interpretations. Here we denote the logarithm of the mass of high-skilled workers employed in city c at time t as h_{ct}, while ℓ_{ct} is the corresponding notation for low-skilled workers.

At time $t = 0$ the two cities are part of the Soviet Union which, for exogenous reasons, attributes to s (but not to z) the status of Science City. As a consequence of this, the government allocated proportionately more high-skilled workers to s, so that $(h_{s0} - h_{z0}) > 0$. At the same time, since in the Soviet Union economic activity was highly segregated geographically, this implies $(\ell_{s0} - \ell_{z0}) \leq 0$. A final consequence of Science City status is that the urban planning choices and the public investments associated with the policy might have made Science Cities a more enjoyable location to live in. In Urban Economics parlance one would say, then, that the amenities a_s of Science City s are higher than the amenities a_z of the ordinary locality z: hence $\tilde{a} \equiv a_s - a_z \geq 0$.

At time $t = 1$ the two cities are part of modern Russia, a market economy, and workers of both types self-select into either location. Following Moretti (2011, 2013) we express the logarithmic indirect utility u_{nic} of an individual i of type $n = h, \ell$, obtained from living in city $c = s, z$, as:

$$u_{nic} = w_{nc} - r_c + a_c + e_{nic} \tag{1}$$

where w_{nc} is the log-wage earned by workers of type n in city c, r_c is an index of local prices (such as housing rents), while e_{nic} denotes the idiosyncratic taste of individual i for city c. For simplicity, here we assume that local prices are identical in the two locations, that is $r_z = r_s$. If r_c represents rents, this could follow if houses are supplied completely elastically in two competitive markets employing the same technology. In fact, we also abstract from congestion effects *à la* Glaeser and Gottlieb (2008, 2009) and any kind of negative externalities that may depend on a city's population. This allows to focus our discussion on the interplay between labor supply and agglomeration effects.

We model the relative preferences of individuals for the two localities as follows:

$$e_{nis} - e_{niz} \sim U\left[-m_n + b_n, m_n + b_n\right] \tag{2}$$

here, for both types $n = h, \ell$, m_n represents the overall degree of mobility of workers of type n – intuitively, the higher m_n the lower the importance of idiosyncratic tastes for the choice of location – while b_n is the type-specific average bias towards Science City s. In Moretti (2011, 2013) it is maintained that $b_h = b_\ell = 0$, however here we assume that:[10]

$$\begin{aligned} b_h &= b\left(h_{s0} - h_{z0}\right) > 0 \\ b_\ell &= b\left(\ell_{z0} - \ell_{s0}\right) \leq 0 \end{aligned} \tag{3}$$

where $b(\cdot)$ is an increasing monotone function with $b(0) = 0$. This hypothesis introduces a mechanism of path-persistence: if an individual used to reside in a specific city during Soviet times, she is likely to prefer to stick there. Consequently, the average bias of workers of a given type depends on their relative allocation at $t = 0$. Another interpretation of (3) is in terms of restrictions to mobility: in Russia, internal mobility used to be very costly if not altogether impossible, due to regulation inherited from Soviet times.[11] This can be represented as a differential, between the two groups, in the average moving cost.

[10] A careful reader will have noted that allowing $b_h, b_\ell \neq 0$ is omothetic to letting the value of amenities vary by worker type, as in Moretti. We feel that in this institutional context, it is important – for the sake of interpreting the empirical evidence – to make a mechanism of path-persistence in location choice explicit in our conceptual framework.

[11] A system of internal visas was in place until the early 2000s. Studies about internal migration rates in Russia in the 1990s show that they were very low (Andrienko and Guriev, 2004; Friebel and Guriev, 2005).

Finally, to close the model we introduce two types of firms: those that employ skilled labor, and those who rely on workers of the low type instead. While in Moretti's analysis this was largely a simplification meant to abstract from the degree of substitutability between skills, this characteristic of the model can be given here a contextual interpretation: if workers of type h are researchers, type-h firms correspond with the R&D sector, while type-ℓ firms represent the rest of the local economy. The log-output y_{nc} of type-n firms in city c is determined according to a Cobb-Douglas technology:

$$\begin{aligned} y_{hc} &= x_{hc} + \theta_h h_c + \mu h_c + \left(1-\mu\right) k_{hc} \\ y_{\ell c} &= x_{\ell c} + \theta_\ell h_c + \mu \ell_c + \left(1-\mu\right) k_{\ell c} \end{aligned} \tag{4}$$

where x_{nc} is the city- and type-specific total factor productivity, while k_{nc} is the log-capital employed by the firms of type n in city c. The supply of capital is infinitely elastic and its cost is the same for all firms in the two cities s and z. For simplicity, the elasticity of labor is equal to $\mu \in (0,1)$ for both types of firms in both cities. Note that firms of type ℓ do not hire workers of type h, but take h_c as given.

The interpretation of parameters $\theta_h \geq 0$ and $\theta_\ell \geq 0$ is as follows. For type-h firms, $\theta_h > 0$ allows for increasing returns due to knowledge spillovers: since the productivity of high-skilled workers grows more than proportionately to their number, this introduces an agglomeration force in the economy. Note that $\theta_h = 0$ implies constant returns to scale in type-h firms. If knowledge spillovers also operate between firms, and the size of the local skilled workforce can affect the productivity of the less skilled workers as well, then $\theta_\ell > 0$. Such a distinction between "restricted" and "general" spillover effects is, to the best of our knowledge, new in theoretical frameworks of urban economics. We find it worthwhile to introduce it, since the model provides different equilibrium predictions to the extent that $\theta_h > 0$, $\theta_\ell > 0$, or both – with corresponding empirical implications.

3.2 Spatial Equilibrium

We now turn to the description of the $t = 1$ equilibrium. In a spatial equilibrium, some marginal worker of either type must be indifferent between cities s and z. This implies that the supply of, say, high-skilled labor in either city is determined by the following condition (I drop timing subscripts for convenience):

$$m_h \left(\frac{h_s - h_z}{\overline{h}} \right) = w_{hs} - w_{hz} + \tilde{a} + b_h \tag{5}$$

where $\overline{h} \equiv h_s + h_z$ is given and such that $\overline{h} < \theta_h^{-1} \mu m_h$.[12] The equilibrium wage differentials $(w_{hs} - w_{hz})$ are obtained as the difference between the marginal productivity of high-skilled labor in the two cities; this difference, in turn, depends on the equilibrium in the capital market.[13] A symmetric analysis applies to the case of low-skilled labor.

As a result, the relative difference in equilibrium high-skilled employment between the two cities can be expressed as:

$$(h_s - h_z) = \frac{\left[\tilde{x}_h + \mu\left(\tilde{a} + b_h\right)\right]\overline{h}}{\mu m_h - \theta_h \overline{h}} \geq 0 \tag{6}$$

where $\tilde{x}_h \equiv x_{hs} - x_{hz}$ is the difference in log-TFP of type-h firms between the two cities. Equation (6) is interpreted as follows: there are three forces that cause Science Cities to continue hosting a larger number of researchers and high-skilled workers after the transition. These are: *i.* inherent productivity differentials $(\tilde{x}_h > 0)$, *ii.* superior amenities in Science Cities $(\tilde{a} > 0)$, and *iii.* path-dependence mechanisms $(b_h > 0)$. All these forces are stronger the more high-skilled workers are mobile (lower m_h) and the larger are the agglomeration effects (larger θ_h). Importantly, agglomeration effects alone are not sufficient to cause employment differentials, at least in the equilibrium under analysis: they only complement those factors (*i.*-*iii.*) that affect the supply of labor.

The relative difference in the productivity of high-skilled workers equals that of their wages:

$$\left(y_{hs} - y_{hz}\right) - (h_s - h_z) = (w_{hs} - w_{hz}) = \frac{m_h \tilde{x}_h + \theta_h \overline{h}\left(\tilde{a} + b_h\right)}{\mu m_h - \theta_h \overline{h}} \tag{7}$$

this result bears some important implications for our empirical analysis. First, absent agglomeration forces $(\theta_h = 0)$ these differences are proportional to the log-TFP differentials $\tilde{x}_h$. Second, if the latter are null $(\tilde{x}_h = 0)$ any positive difference in the productivity and wages of high-skilled workers between Science Cities and comparable locations is indicative of increasing returns.[14] In our empirical analysis we measure the difference

[12] This condition is necessary to avoid that the denominators of (6) and (7) turn negative, breaking their interpretability. In practice, spillovers θ_h and the total mass of log-researchers $\overline{h}$ cannot be simultaneously "too high," or the equilibrium would degenerate into full spatial concentration of high-skilled workers.

[13] Equilibrium in the capital market implies that the marginal productivity of capital must be equal in the two cities: $(k_{hs} - k_{hz}) = (h_s - h_z) + \mu^{-1}\tilde{x}_h$. This lets express the difference between the inverse labor demands in the two cities as: $(w_{hs} - w_{hz}) = \mu^{-1}\left[\tilde{x}_h + \theta_h\left(h_s - h_z\right)\right]$.

[14] Intuitively, under constant returns to scale $(\theta_h = 0)$ the endogenous response of capital would equalize differences across the two cities in both the marginal and the average product of (high-skilled) labor, even in presence of employment differentials.

in municipal-level outcomes, observed about 20 years following the dissolution of the USSR, between several dozens of Science Cities and their matched counterparts. Thus, by standard statistical arguments it is unlikely that exogenous shocks to TFP alone could explain any systematic productivity or wage differentials for high-skilled workers.

For low-skilled workers, the equilibrium log-employment difference reads (for given $\overline{\ell} \equiv \ell_s + \ell_z$) as:

$$(\ell_s - \ell_z) = \frac{\overline{\ell}}{m_\ell} \left[\frac{\tilde{x}_\ell + \theta_\ell (h_s - h_z)}{\mu} + \tilde{a} + b_\ell \right] \gtreqless 0 \tag{8}$$

and its sign is undetermined. In fact, path-persistence mechanisms that *may* push low-skilled workers away from Science Cities ($b_\ell \leq 0$) could be more than compensated by: amenity differentials ($\tilde{a} \geq 0$), TFP differentials ($\tilde{x}_\ell \equiv x_{\ell s} - x_{\ell z} \geq 0$), and, if Science Cities host more high-skilled workers, cross-sector agglomeration forces ($\theta_\ell (h_s - h_z) \geq 0$). The equilibrium differentials in productivity and wages for low-skilled workers are:

$$\left(y_{\ell s} - y_{\ell z}\right) - (\ell_s - \ell_z) = (w_{\ell s} - w_{\ell z}) = \frac{\tilde{x}_\ell + \theta_\ell (h_s - h_z)}{\mu} \tag{9}$$

hence, by a reasoning analogous to the one outlined in the case of high-skilled workers, any empirical difference in those variables – in sectors unrelated to R&D – is evidence favorable to the operation of "generalized" spillover effects ($\theta_\ell > 0$).

All these results would still hold, in qualitative terms, if rents or congestion effects were allowed to vary by city and to depend on a city's total population. In this case real wage differentials would be smaller than nominal wage differentials, thereby restraining labor mobility in equilibrium. See Moretti (2011, 2013) for a full-fledged analysis of this model with negative locational externalities but without positive agglomeration forces.

4 Data and Descriptive Statistics

We evaluate the long-run effects of Science Cities by employing a unique dataset, which contains information previously unavailable in electronic format. Specifically, it combines: *i.* our database on Science Cities, which is described in Section 2 and reported in the Data Appendix; *ii.* municipal-level data that aggregate various sources about historical and current characteristics of Russian cities; and *iii.* a firm-level database that is obtained by merging BEEPS V Russia and Bureau van Dijk's Orbis data. In what follows, we separately detail on the latter two.

4.1 Municipal-level Data Sources and Construction

We construct a municipal-level dataset for all Russian municipalities (2333 in total).[15] We obtain administrative data from official sources, and we merge municipalities to different types of information through GIS softwares. We manually assign Science City status to each municipality; in total the data include 88 municipalities with at least one Science City.[16] In a few cases historical and current municipal boundaries do not match exactly, thus we clean our data manually. Data types and sources are described in more detail in the Data Appendix; here we briefly summarize them by distinguishing – for the sake of clarity – between current socio-economic outcomes, data about recent municipal budgets, geographical characteristics and historical variables.

Current Outcomes. Our variables of interest about current characteristics of Russian municipalities match the main outcomes of interest from our theoretical framework. Specifically, we extract data about the overall municipal population, the share of the population that attained higher education qualifications, and the share of the population that completed any form of postgraduate education from the 2010 Russian Census.

We proxy innovation by the total count of local inventor addresses that appear on patents applied to the European Patent Office (EPO) between 2006 and 2015. Each address is weighted by the inverse of the number of inventors that appear on the relevant patent; we call this measure (local) *fractional patents*. We also divide this measure by the total number of a city's inhabitants holding a postgraduate qualification, so to obtain a proxy for average researchers' productivity. In addition, we examine information about total employment and per-capita wages in the combined R&D-ICT sectors; this is obtained from the Russian Statistical Office (ROSSTAT). Note that ROSSTAT data of any kind are typically never available for closed cities, arguably because of considerations of Russian national security.

Finally, as accurate GDP data at the municipal level is unavailable in Russia, we use several proxies for economic activity: average night lights intensity observed by satellites

[15]In this paper, we use the English term "municipality" to denote the *municipal'nye obrazovaniya* of Russia, i.e. units at the second administrative level (akin to U.S. counties). We use the word "region" to refer instead to federal subjects (*oblast'*, *kray* or *respublika*) i.e. units at the first administrative level.

[16]NAS (2002) lists four Science Cities for which only their Soviet-era nomenclature is publicly available: Krasnodar-59, Novosibirsk-49, Omsk-5 and Perm-6. Their exact location is still unclear; thus we exclude these four places from the analysis as they cannot be matched to any municipality. In addition, three pairs of Science Cities are located within the same municipalities. Hence, 91 Science Cities are mapped to 88 municipalities with at least one Science City.

in 1992-1994 and in 2009-2011,[17] as well as a number of variables concerning local Small and Medium Enterprises (SMEs) from the 2010 SME census by ROSSTAT. In particular, we examine the overall number, the density and the labor productivity of SMEs, either across all sectors of the economy or specifically in manufacturing.

Municipal Budgets. Similarly as von Ehrlich and Seidel (2015), we also analyze information about the budgets of Russian municipalities, which can be accessed through ROSSTAT for 2006-2016. On the revenue side, we are able to differentiate between direct revenues (e.g. from local taxes) and transfers from both the federal and regional governments. In addition, we are able to distinguish local expenditures by category, such as education, healthcare, local infrastracture, *et cetera.* All measures are converted to 2010 prices using ROSSTAT's official CPI indices.

Geographical Characteristics. We collect or calculate municipal-specific information about several geographical characteristics: municipal area, average altitude, as well as and average temperatures in January and July. Since locating close to large amounts of water was necessary for Science Cities of certain specializations, we also collect data on each municipality's access to the coast, to a major river or to a major lake.[18]

Historical Variables. For the sake of matching Science Cities to other municipalities that were similar to them at beginning of the Cold War, we collect a number of historical information about Russian municipalities. To account for differences in city size we use population data from the first post-World War II census held in the Soviet Union, which was conducted in January 1959.[19] Since the 1959 census does not break population data by educational achievement at the municipal level, we use data on the number of higher education institutions located in a municipality in 1959 (De Witt, 1961), as well as that on the number of local R&D institutes in 1947 (Dexter and Rodionov, 2016), in order to proxy for the pre-existing human capital of an urban area.

To control for the existing level of industrial development in a municipality, we use

[17] Night lights can plausibly be used as a proxy for economic activity under the assumption that lighting is a normal good; see Donaldson and Storeygard (2016). Examples of economic studies employing night lights as a proxy for economic activity within geographic units for which no alternative data source is available include Hodler and Raschky (2014) and Storeygard (2016).

[18] For each municipality, we code this information both as dummy variables (presence or absence of either fresh or salted water within the municipal territory) and as the distance between the municipality's geographical centroid and the closest source of water in question.

[19] We would prefer to use population data from the 1940s but there was no census conducted until 1959; moreover, World War II affected the Russian demography so much that any figures collected before 1941 are inadequate.

two pieces of information. The first is the number of plants of the Soviet defense industry (factories, research and design establishments) which are located in each municipality in 1947 (Dexter and Rodionov, 2016). The second is the number of local branches of the State Bank of the USSR in 1946, obtained from the archives of the Bank itself: this institution was an instrument of the Soviet economic policy, and the geographical dispersion of its branches can be seen as indicative of an area's importance for the Soviet developmental strategies; see also Bircan and De Haas (2017). Moreover, most Science Cities needed access to good transportation links, while others had to be located in remote areas far from espionage threats. To account for both factors we use GIS data about Russian railroads in 1943[20] and about the post-WWII USSR borders.[21]

Summary Statistics. Table 1 displays summary statistics for municipal-level characteristics and outcomes, distinguishing between municipalities hosting Science Cities and all other ordinary municipalities. It shows that, on average, Science Cities were located in more populous and warmer places, with a higher historical concentration of industrial plants, universities, and R&D institutes. In addition, all our current outcome variables register positive and significant differences.

4.2 Firm-level Data Sources

To perform our firm-level analysis, we use the fifth round of BEEPS merged with Bureau van Dijk's Orbis database – both for Russia only. BEEPS is a firm-level survey conducted by the European Bank for Reconstruction and Development and the World Bank. It is based on face-to-face interviews with 4,220 managers of registered firms with at least five employees.[22] Stratified random sampling is used to select eligible firms to participate in the survey. While the survey was limited to a subset of all the Russian regions, those that were chosen encompass the majority of historical Science Cities, as shown in Figure 2. The database contains geographic coordinates of the firm's location, based on which we can determine distances from Science Cities.

[20] In the Soviet economy, railroads were the workhorse of the transportation network; road transport played only a secondary role (Ambler et al., 1985). Most of the railroads' construction took place in tsarist Russia; even in Soviet times railroads were not important just for transportation and mobility, but also as drivers of regional industrialization. Using information about the railroad network in 1943 is preferable to later dates, because the Soviet rail transport became one of the most developed in the world after World War II, driven by the country's need to extract – and transport – its natural resources.

[21] Similarly as with the water-related variables, we record information related to historical railroads or the USSR borders both as dummies and as distances from the municipal centroid.

[22] The main objective of BEEPS is the assessment of the business environment across different regions.

Outcomes. BEEPS V included, for the first time, an innovation module. This provides information as to whether, in the last three years prior to the survey a firm engaged in in-house or outsorced R&D; if it introduced a new product, process or technological innovation, and whether it was granted any patent. We manually clean the information contained in the innovation module: for each firm, we verify whether survey responses match the firm's main product and industry, by also employing external information about the individual firms.[23] Moreover, we are able to match about 75% of BEEPS firms to Orbis accounting data, which gives us access to additional measures of economic performance (labor productivity and operating revenue) for a subset of firms.

Controls. BEEPS V Russia contains measures for several firm characteristics, such as: age; industry; exporter status; ownership; geographical scope of the main market (regional, national or international); exporter status (direct or indirect); the number of permanent full-time employees; the share of employees with a university degree. In addition, geographic coordinates let us control for the size of the city where firms operate.

Summary Statistics. Table 2 reports descriptive statistics at the firm level. Notably, a sizable fraction of firms (21.6%) reports at least some type of innovation in the last three years prior to the survey; however the fraction of firms performing R&D is lower (11.1%). About one third of the firms in our sample are in manufacturing. The closest Science City for our firms is, on average, distant 154km; not much in the Russian landscape.

5 Empirical Methodology

In this section we outline our two empirical strategies for, respectively, our municipal-level and our firm-level analyses. In what follows, we discuss them both separately.

5.1 Municipal-level Analysis

We compare the long-run outcomes Y_{cq} of municipalities hosting Science Cities against those of other municipalities (that we call "ordinary" municipalities) that in the years following World War II were similar to Science Cities in terms of geographical and socio-economic characteristics X_{ck}. Here $c = 1, \dots, N$ indexes municipalities; $q = 1, \dots, Q$ our

[23] We also compare the descriptions of the main new product or process reported in the survey with the definitions given in the Oslo Manual (OECD and Statistical Office of the European Communities, 2005), removing those that do not match.

long-run outcomes of interest; and $k = 1, \ldots, K$ the geographical and historical characteristics we control for. For each long-run outcome, we estimate the Average Treatment Effect on the Treated (ATT) as in a standard program evaluation framework, with the treatment being the historical establishment of a Science City in a municipality.

Our identifying assumption is that, conditional on the observed geographical and historical characteristics, the establishment of Science cities did not depend on factors that would affect future outcomes. The rationale of the Conditional Independence Assumption is provided here by our previous discussion about the location of Science Cities. In particular, we consider those military, strategic and generally idiosyncratic factors that typically affected the choice of Soviet planners as unobservables, orthogonal to current outcomes. Similarly, the choice of observable characteristics we match upon is also based on the historical evidence discussed in Section 2: we control for the level of economic development, human capital, accessibility and the presence of certain natural features using the historical data that we assembled. Importantly, we also account for "closed city" status: we match Science Cities that were closed to ordinary municipalities that were also closed, and symmetrically for non-closed cities.

Our matching algorithm of choice is Mahalanobis matching, by which a Science City s is matched to the ordinary municipality z with the lowest *Mahalanobis Distance* m_{sz}:

$$m_{sz}(\mathrm{x}_s, \mathrm{x}_z) = (\mathrm{x}_s - \mathrm{x}_z)^{\mathrm{T}} \Sigma (\mathrm{x}_s - \mathrm{x}_z) \tag{10}$$

where x_c is the vector of all observable covariates for municipality $c = s, z$; while Σ is the empirical covariance matrix of the covariates. Matching is performed with replacement, so that a control municipality can be linked up to multiple treated cities; in addition, it is conditional upon exact matching on certain dummy variables, that is access to inland water, coastal city status and closed city status. With respect to other typical matching methods, such as Propensity Score Matching (PSM), we feel that Mahalanobis matching allows to better handle the geographical dimension of this setting. In fact, we include municipal coordinates into vector x_c, requiring that Science Cities are matched to places close in space, so to mitigate concerns about the effect of area-specific unobservables. We also replicate our analysis using PSM, which produces ATT estimates that are usually slightly larger than in the Mahalanobis case (they are available upon request).[24]

[24] Relative to PSM, however, Mahalanobis matching has its own drawbacks: it is known to perform worse with a high number of covariates, or when covariates are not normally distributed (Gu and Rosenbaum, 1993; Zhao, 2004). In order to improve on the quality of matching, we calculate Mahalanobis distances

Our sample of treated observations varies across different ATT estimates, for two reasons: first, specific information for certain municipalities – like closed cities – is not publicly available; second, we perform robustness checks such as the removal of modern *Naukogrady* from the analysis. For each subsample we replicate our matching algorithm, and obtain different sets of treated-control matches.[25] For all our outcomes we estimate the ATT with and without the correction for the multiple covariates bias, and we perform statistical inference by calculating standard errors based on conventional formulae (Abadie and Imbens, 2006, 2011). Since our coverage of Russian municipalities equals or approximates the universe we do not apply sampling weights.

5.2 Firm-level Analysis

In our firm-level analysis, we estimate a number of probit models with the following latent variable representation:

$$I^*_{fr} = \beta_0 + \sum_{d=1}^{D} \beta_d W_{fr,d} + \gamma \underbrace{\sum_{s=1}^{S} \exp\left[-\lambda \cdot \mathrm{dist}\left(f,s\right)\right] H_s}_{\equiv G_{fr} = G_{fr}(H_1,\ldots,H_S;\lambda)} + \eta_r + \varepsilon_{fr} \tag{11}$$

where $f = 1,\ldots,F$ indexes firms; $s = 1,\ldots,S$ denotes Science Cities; r is a subscript for Russian regions; I^*_{fr} is the latent variable associated with one specific innovation binary outcome I_{fr}; $\mathrm{dist}\left(f,s\right)$ is the geodesic distance between firm f and Science City s; $\left(W_{fr,1},\ldots,W_{fr,D}\right)$ are D controls available in the data (see Section 4); H_s is some relevant characteristic of Science City s; η_r is a region fixed effect; and finally ε_{fr} is an error term which is distributed as a standard normal. In addition, we estimate via OLS a linear version of (11):

$$\log P_{fr} = \tilde{\beta}_0 + \sum_{d=1}^{D} \tilde{\beta}_d W_{fr,d} + \tilde{\gamma} G_{fr} + \tilde{\eta}_r + \upsilon_{fr} \tag{12}$$

where P_{fr} is either the firm's operating revenue (sales), or labor productivity. Functional forms that involve a term akin to G_{fr} are routinely adopted in studies of R&D spillovers (Lychagin et al., 2016) or of agglomeration effects between firms (Drucker, 2012).

using the logs of covariates with highly asymmetric empirical distributions. In the case of covariates X_{ck} that can take zero values (such as the historical number of plants, universities or R&D institutes) we use the corresponding quantity $x_{ck} = \log(X_{ck} + 1)$.

[25]The differences are due to the removal of certain ordinary municipalities, such as closed ones, from the raw sample on which matching is performed. However, we find these differences negligible.

In probit regressions, the main parameter of interest is γ, which measures the relationship between the innovation of firm f and the characteristics H_s of all Science Cities s, weighted by the relative geographic proximity between f and each s. To more easily interpret the empirical model, observe that $\exp\left[-\lambda \cdot \text{dist}\left(f, s\right)\right]$ is the exponential decay of a Science City's "influence" in space: it is equal to 1 if a firm locates right in the center of a Science City, and it is negligible unless firm f and city s are relatively close. Thus, if a firm is located in a relatively isolated Science City, the quantity $\gamma \cdot \hat{\phi}_f$ – where $\hat{\phi}_f$ is the standard normal density function evaluated at the parameter estimates and at firm f's values of the RHS variables – approximates the marginal effect of the characteristics H_s of Science City s on the probability of a positive realization of I_{fr} for firm f. Similarly, in linear models $\tilde{\gamma}$ is more easily interpreted as the average change in P_{fr} for firms that are located in a "relatively isolated" Science City with characteristics H_s.

These specifications are flexible, and vary with the choice of H_s and parameter λ. For both linear and non-linear models, we analyze the dependence of our outcomes of interest with different "agglomeration measures" based on three alternative characteristics H_s of a Science City that likely relate to its innovation potential. These are: the fractional patents produced in Science City s, the graduate share of its population, and its post-graduate share. Descriptive statistics and cross-correlations for the resulting firm-level agglomeration measures G_{fr} are displayed in Tables 3 and 4, respectively. We analyze each measure in isolation, or by including all three in the same regression; in addition, in some specifications we interact G_{fr} with a manufacturing/services dummy in order to evaluate whether parameter γ (or $\tilde{\gamma}$) varies by macro-sector. In our main empirical analysis we set $\lambda = 1$; however, we obtain similar results with higher values for this parameter (results obtained when setting $\lambda = 2$ or $\lambda = 5$ are available upon request).

While we do not attempt to give any causal interpretation to our firm-level results, we observe that the concerns of endogeneity are limited in this setting. Since the creation of Science Cities predates the establishment of most modern Russian firms – virtually all in our sample – the only way for the distance-based regressor and the error term to be correlated is if a Science City "attracts" or otherwise encourages the location of more innovative or better performing firms in their proximities. Still, we make no attempts to correct for this possible instance of endogeneity. Our interest, in fact, is about evaluating in a descriptive sense whether any relationship between Science Cities and firm-level outcomes extends in space, and we do not intend to remove a potential mechanism by which such relationships may manifest themselves.

6 Empirical Results at the Municipal Level

In this section we illustrate the results of the municipal-level empirical analysis. After describing our matched sample we present our main results. Subsequently, in order to shed more light on the mechanism driving these results, we discuss estimates restricted to the non-*Naukogrady* subsample, as well as results about additional outcomes, such as municipal budget variables and demographic variables split by cohort of birth.

6.1 Quality of Matching

Our main matching sample is constituted by 85 municipalities that include a Science City, as well as by 65 matched municipalities which do not host any Science City. Figure 3 displays the matched pairs on the map of Russia. Out of 88 Science City municipalities in our original data, 3 are not matched to any control observation. On the other hand, most controls observations are matched to at most two Science Cities (three in a couple of cases). As we expect from Mahalanobis matching when including municipal coordinates among the covariates, Science Cities and their counterparts are matched – with a few exceptions – relatively close in space, especially in the more densely populated and more developed areas of Russia. In particular, municipalities close to Moscow are typically matched to other municipalities that are also close to Moscow, which mitigates concerns about the proximity of many Science Cities to the capital of Russia.

Table 5 displays the standardized mean difference and the variance ratio between treated and control observations, both in the original and in the matched samples. The table shows that matching achieves a remarkable degree of balance in both the first and the second moment, despite the rigidity of the Mahalanobis algorithm and the other requirements that we have imposed on matching (in particular, closed Science Cities are matched to non-Science closed cities, and vice versa). In order to perform estimates for outcomes that are missing for some municipalities, or when modern *Naukogrady* are excluded from the analysis, we construct matching samples based on a subset of Science Cities; these samples are characterized by a similarly good degree of covariate balance.

6.2 ATT Estimation: All Science Cities

The main estimates of the ATT for our twelve outcomes of interest are reported in Table 6. In what follows we summarize our results, starting from the demographics variables extracted from the 2010 Russian Census. Science Cities seem to be, on average, slightly more populated than their matched counterparts, by about 24,000 people. This difference, however, is only weakly statistically significant (at the 10% confidence level), and it is driven for the most part by the more educated segments of the population. In fact, the share of inhabitants holding a university degree is higher by about 5.5 percentage points in Science Cities; similarly, Science Cities still host today more people with some postgraduate qualification (by 0.2 percentage points). Both differences are statistically significant at the 1% level. Note that all estimates about these demographic variables are substantially smaller than the naive differences.

We now turn our attention to innovation measures. Our absolute fractional patents measure is estimated positive and statistically significant (at the 1% level), similarly as the corresponding average measure (significant at the 5% level). These results indicate that between 2006 and 2015, Science Cities have applied to the EPO, on average, for 11 more fractional patents than their matched municipalities, or about 0.7 more fractional patents for each individual with a postgraduate degree.[26] Note that our ATT estimates are virtually identical to the raw differences for both patent measures, which is arguably due to the fact that R&D is very spatially concentrated, in Russia as in other countries. Indeed, by analyzing ROSSTAT data it appears that high-tech sectors of the economy are more developed in Science Cities, since both measures of employment and salaries in the combined R&D-ICT sectors register positive and statistically significant differences. In those industries, Science Cities provide jobs for about 2,300 more people, paying a monthly salary higher by about 8,000 roubles (roughly $250) at the 2010 prices.

We finally examine our proxies of overall economic activity. Night lights indicators measured around 2010 register a high and statistically significant difference in favor of Science Cities (while the raw difference is about threefold). ROSSTAT's SME Census provides a different kind of information. While raw differences suggest that Science Cities are characterized by a overall higher diffusion of SMEs, the corresponding ATT estimates – either relative to all sectors of the economy, or specific to manufacturing – are not statistically different from zero. Similar results, which are not displayed in Table 6 for brevity, are obtained for measures of SME density, (number of SMEs by municipal population). The ATT on the labor productivity of SMEs is, however, estimated positive and statistically significant, both when pooling all industries and when specifically analyzing manufacturing (in both cases, ATT estimates are about one half of the naive differences).

[26] We obtain similar results if we use absolute, as opposed to fractional, measures of patent output.

In an anticipation of our later discussion, we argue that the results seem to point to an economic effect of Science Cities that operates on the intensive (productivity) margin.

We also perform a sensitivity analysis of our ATT estimates, following Rosenbaum (2002). Specifically, we simulate the presence of some unobserved factors that would affect both the outcomes and the probability of receiving the treatment, and we assess to what extent this would influence our conclusions about the presence of statistically significant differences in Y_{cq} between treated and (matched) control observations, for all outcomes $q = 1, \ldots, Q$. The size of the simulated unobserved factor is given by parameter $\Gamma \geq 1$, which measures the hypothesized odds of receiving the treatment ($\Gamma = 1$ in an experimental setting). In Table 6 we report, for each outcome variable, the lower value Γ^* that leads to inconclusive tests about the presence of a statistically significant difference between treated and control observations.[27] The values of Γ^* are very high (around 3) for the census variables, our patent outcomes, the employment and salary measures in R&D and ICT, as well as the night lights measure. They are satisfactorily high (around 2) for the measures of SME labor productivity; as expected, they are close to 1 for the SME count measures.[28] These results are in line with our statistical inference about the estimated ATT parameters, and show that our qualitative results are very robust to possible threats to identification.[29]

We interpret our results in light of our analytical framework presented in Section 3. In the model, high-skilled population and employment in high-tech sectors can be driven by some mechanism of long run persistence which traces its roots in the Soviet-era allocation of workers across different cities. For example, high-skilled workers might simply prefer to live in Science Cities because they consider them their home, because moving is costly, or because Science Cities are inherently preferable. Agglomeration forces such as localized knowledge spillovers can reinforce and complement such factors. However, productivity and wages can only be higher in Science Cities because of agglomeration forces, or due to some other exogenous factors that are unaccounted by the model. Since

[27]We set a 5% type I error. More specific results of the sensitivity analysis are available upon request.

[28]To give context, $\Gamma = 2$ indicates a simulated unobserved factor that doubles the probability of receiving the treatment relative to that of not receiving it, or vice versa; such a high value of Γ would be realistic only in presence of very serious threats to our conditional independence assumption. Consequently, very high "critical" values of Γ^* associated with a certain outcome – close to 2 or higher – indicate that the results are likely to be very robust to such threats.

[29]At a first glance, it may seem counterintuitive that $\Gamma^* > 1$ in the case of outcomes, such SME count measures, whose ATT is estimated not statistically different from zero. However, the latter is a conclusion derived from a parametric test, while the sensitivity analysis is based on non-parametric Wilcoxon signed-rank tests. In practice, it is unlikely that the two procedures lead to very divergent conclusions.

we trace the differential evolution, over 20 years following the dissolution of the USSR, of a number of pairs of matched cities that varies between 63 and 83, we are not inclined to believe that exogenous shocks alone can drive the results that we observe for average patent production, wages in high-tech sectors, and SME labor productivity. Conversely, we interpret this evidence as favorable to the existence of increasing returns to the co-location of high-skilled workers ($\theta_h > 0$), which possibly spills over lesser skilled ones as well ($\theta_\ell > 0$) as hinted in particular by the results about SME labor productivity.

Finally, it must be mentioned that while our results are based on one-to-one matching, the main qualitative conclusions are not altered in the case of one-to-many matching. In fact, increasing the number of matched nearest neighbors usually increases bias in exchange for a reduction in variance, and thus may result in a higher number of ATT parameters being estimated statistically significant (possibly incorrectly). We have obtained similar results by increasing the number of nearest neighbors up to five; however, we do not present these results here due to space limitations.

6.3 ATT Estimation: Historical Science Cities

Our interpretation of the estimated long run consequences of Science Cities, which rests on the interaction between persistence and agglomeration forces, would be threatened if, on average, Science Cities still receive today a differential treatment from the Russian government, in the form of direct or indirect support to local R&D or other economic activities. Within our analytical framework, this is isomorphic to the case where the random shocks $\tilde{x}_h$, and possibly $\tilde{x}_\ell$, have a nonzero mean. In order to assess, to a first degree of approximation, to what extent our results depend on current governmental support, we perform an additional analysis which is largely similar to the one discussed above, with the exception that it excludes those Science Cities with the official status of *Naukogrady* in today's Russia. For these fourteen Science Cities, the Russian government has resumed the Soviet-era program in recent years, although with a less military and more civil focus. By contrast, we call the remaining Science Cities "historical."

For brevity, we jump directly to the empirical estimates reported in Table 7, which are also based on one-to-one Mahalanobis matching, and we compare them to those from Table 6. We find the results striking. In fact, the estimated ATT is, for most outcomes of interest, very similar to the corresponding estimates from Table 6, if usually slightly smaller. Statistical inferences and sensitivity analyses *à la* Rosenbaum generally confirm our former assessment.[30] The only outcomes for which the removal of *Naukograday* results in a substantial change of the estimated effects are the patent outcomes. In the case of the fractional patent count, the estimated ATT is about one half the former estimates; as for the average fractional patent measure, it is about 70% smaller. Nevertheless, the estimates for both outcomes remain significant at the 1% level and robust, as evidenced by a Γ^* well above 2. Notably, the employment and salary measures relative to the R&D and ICT sector remain very similar to the previous ones.

Our reading of the restricted analysis is as follows. The smaller estimated effects on the patent outcomes can be explained in two non exclusive ways. On the one hand, in an institutional context such as that of Russia innovation is still predominantly driven by the government sector, and our patent measures reflect the importance of renewed state support to R&D in selected localities. On the other hand, it is possible that in resuming a restricted version of the older Science Cities program, the Russian government has chosen the best former Science Cities in order to make them the newer *Naukograday*. In either case, we keep observing a positive differential in favor of historical Science Cities for most demographic and economic outcomes of interest. Such differentials are even more surprising as they are clearly independent of the extent to which the government supports local R&D *today*, and thus can only interpreted as long run effects of some sort. Therefore, we find that our previous interpretation of the empirical results is if anything reinforced from this restricted analysis.

6.4 ATT Estimation: Municipal Budgets

We now turn our attention to the analysis of municipal budget of Science Cities; specifically, we compare certain aggregate entries of the budget of Science Cities to those of their matched counterparts. The objective of this analysis is twofold. First, this lets us test the extent to which Science Cities, be they historical or current *Naukograday*, receive a differential amount of direct governmental transfers. In addition, we see this as an opportunity to uncover potential drivers of our results. In the analysis of subsidized border West German municipalities by von Ehrlich and Seidel (2015) that we mentioned in the introduction, the authors explain their results not by agglomeration forces, but through the persistence of municipal spending in certain, presumably productivity-enhancing,

[30] In the case of labor productivity for manufacturing SMEs, the ATT is estimated statistically significant at the 1% level, but Rosenbaum's $\Gamma^* = 1.20$ raises a warning sign. In fact, the estimated ATT effect is largely driven by a subset of matched pairs with large differences for the outcome in question.

infrastructures. A parallel mechanism could be at work in our setting: for example, since Science Cities used to be inhabited by relatively more university graduates than other similar localities, their population might have kept a stronger preference for the provision of certain public goods, such as those related to education.

Russian municipalities collect resources from both local taxes (property taxes, merchant fees, fees for the provision of local services) and from a portion of federal taxes (income tax, business tax etc.) that are paid by local residents. In addition, municipalities receive discretional transfers from both the federal and the regional governments. In our data we are able to identify the source of municipal revenues, as well as the allocation of expenditures by category (education, health services, local infrastructures etc.) for all Russian municipalities except closed cities. In order to obtain relevant measures of interest for each municipality, we collapse certain budget items by taking, for each, the municipal average over the 2006-2016 period (normalized to 2010 prices), and then we divide the result by the 2010 municipal population. We estimate the ATT of Science City status on each of these per capita measures, comparing the fiscal and expenditure patterns of Science Cities to those of their matched counterparts.

Our estimates are summarized in Table 8 for both the sample of non-closed Science cities, and the one additionally restricted to historical Science Cities. The results are particularly transparent in the latter case, which we discuss first. In raw differences Science Cities collect, per capita, more taxes than ordinary municipalities; however, they receive disproportionately *less* total transfers: as a result, both their total revenues and expenditures per capita are smaller. When controlling for historically observable characteristics, however, it appears that total revenues and expenditures per capita are equalized. Since Science Cities are able to obtain a statistically significant higher amount of tax revenues per capita with respect to matched localities (as they are richer), this is compensated by less, and statistically significantly so, total transfers per capita. The case of all non-closed Science Cities, including today's *Naukogrady*, is similar. However, all ATT estimates are slightly larger in the wider group, indicating that tax revenues, total transfers and total expenditures per capita are all relatively higher for modern *Naukogrady*.

Our reading of these results, based on our understanding of the institutional context, is that political forces operate for the redistribution of federal resources so to achieve approximately similar levels of governmental expenditures per capita across space. Since Science Cities are typically richer, this results in less total transfers in their favor. While we understand that support to Science Cities may also exist in the form of direct expenditures appearing only in the federal budget – a kind of information which is unfortunately unavailable to us – if historical Science Cities were still of some strategic importance for the federal government we would expect, if anything, to observe less symmetry between revenues and tranfers per capita. In other words, the government may want to complement direct intervention with more indirect subsidies. However, we can only attest limited evidence for such a mechanism in the case of today's *Naukogrady*, which is to be expected if the role of historical Science Cities is, in fact, by all means exhausted.

Finally, we investigate the possible presence of differential expenditure patterns of Science Cities. In particular, we suspected that a more educated population might have demanded stronger investment in education, which in turn could have represented an additional channel through which our main results manifest themselves. However, the estimates about the per capita expenditures in education that are reported in Table 8 do not support this hypothesis; we find no statistically significant differences across other expenditures categories either (we do not show the associated estimates for brevity). To summarize, our analysis of the municipal budgets does not provide evidence in favor of fiscal channels, either in the form of superior governmental transfers or in that of differential expenditure patterns *à la* von Ehrlich and Seidel, to explain our results. In light of this, we maintain that the mechanisms outlined in our model – the interplay between persistence and agglomeration forces – constitute a preferable set of explanations.

6.5 ATT Estimation: Demographic and Economic Dynamics

One final concern about the mechanisms that we postulate for interpreting our results is that they may not be long lasting. Observe that our model analyzes the spatial equilibrium that would emerge in a static context if workers initially allocated across space by a central planner were suddenly allowed to move. In the real world, however, workers are slowly replaced by younger workers from newer generations. In our framework, the persistence forces interacting with spillover effects are modeled as differential preferences between static sets of workers. If new generations do not share the preferences or the characteristics of their fathers, spatial equilibrium can lead over time to mean reversion – even in presence of agglomeration forces, thanks to the action of random shocks. This feature is typical of empirical studies in economic geography, perhaps most famously that by Davis and Weinstein (2002). In this case our results are not to be interpreted as true long run effects, but rather as snapshots of a long transition back to steady state.

We investigate the possibility that the advantage of Science Cities wanes over time by exploiting some additional information present in our dataset. Specifically, our Russian Census data allows to identify the number of residents in each municipality by type of attained education within each cohort of birth. This lets us assess to what extent our results about urban educational levels are mainly driven by older cohorts, or instead substantially depend from younger cohorts as well. To this end, we split the population of each municipality between the "young" (those born after 1965), and the "old" (those born on or before 1965). At the time of the dissolution of the USSR (1991-1992) the older individuals in the "young" group who had obtained a university degree were starting their professional career, and presumably could move more easily. Furthermore, those who were underage at the time of the transition might have pursued less education than their fathers (mean reversion). Both factors would predict a more equal distribution of young graduates between Science Cities and their matched counterparts.

We estimate the ATT of Science Cities on the graduate share of the population separately for the "old" and "young" groups, by exploiting our matched sample. The results are reported in Table 9: we find that while the differences are indeed larger for the older group, they are positive and statistically significant for the younger one, in whose case the effect amounts to about 60% of the old group's. All estimates are uniformly smaller, but still statistically significant, if current *Naukogrady* are removed from the sample. We perform a similar analysis for the postgraduate share; however, in this case we define the threshold year of birth as 1955, taking into account the fact that in Russia, postgraduate education is characterized by a long average duration.[31] In relative terms, the estimates of the two groups compare similarly to those of the graduate share. For neither measure the results depend substantively on the chosen threshold. Thus, this analysis provides little evidence in favor of the mean reversion hypothesis: it appears that the children of Soviet inhabitants of Science Cities pursue educational and locational choices that are largely similar to those of their fathers, albeit not identical.

Following this analysis, a logical next step would be to assess mean reversion in economic outcomes. If the relative skill level of Science Cities and that of comparable municipalities are equalized over time, we would expect economic convergence as well.

[31] We observe a secular increase in the attainment of postgraduate education in Russia following the transition, which is opposite to the general trend observed for tertiary education. Among all municipalities, the unweighted average share of graduates in the old group is about 12.5%, while it amounts to about 11.0 among the younger (24.5% vs. 21.5% in Science Cities). Conversely, the postgraduate share is 0.15% in the old group and 0.33% in the young group (0.50% vs. 0.63% in Science Cities).

Unfortunately, our data do not let us track the evolution of our proxies of economic activity over time, except for one variable: our night lights satellite data. Table 9 also displays the ATT estimates for the average night lights measurements obtained between 1992 and 1994, right after the transition. We ensure comparability with the estimates reported in Tables 6-7 for the 2009-2011 average, by appropriately normalizing both into z-scores. By examining both, one can observe that the estimates relative to 2009-2011 are actually larger than those for 1992-1994, indicating that, if anything, Science Cities have been growing *faster* than their matched municipalities. While this finding may also be due to the possibility that the negative shock associated with the transition disproportionately affected Science Cities, with a resulting ensuing rebound, it hardly supports the hypothesis of mean reversion either. Consequently, we maintain our conclusion that the main results are to be interpreted as persistent long run effects, which have long survived the original policy that has ultimately caused them.

7 Empirical Results at the Firm Level

In this section we discuss our empirical results at the firm level, which are aimed at exploring the "spatial reach" of Science Cities and their consequences on firms' innovation and performance. We separately present estimates of non-linear models based on (11) and of linear models like (12), and we briefly comment on their economic significance.

7.1 Estimates of γ: Binary Innovation Outcomes

Table 10 presents the results from the estimation of several probit models with latent variable representation (11) for five separate firm-level outcome binary outcomes I_{fr}: whether a firm engages in any R&D activity; whether in the three years prior to the survey the firm has produced a relevant innovation (either product or process); whether this was specifically a product, or a process innovation; and finally if the firm's innovation effort has resulted in a patent. On the right-hand side of (11) we employ different agglomeration measures, possibly separated for service and manufacturing firms, as we discuss in Section 5.2. In the table, we present the probit marginal effects, which are interpreted as the increase in the probability of $I_{fr} = 1$ which is associated with a unitary increase in H_s for a firm in a "relatively isolated" Science City s. The relative standard errors are Taylor-linearized to account for survey stratification.

In what follows, we discuss our results for each agglomeration measure. In the case of the patent-based measure, the estimates of γ is positive and statistically significant for three outcome variables: engagement in R&D (1.5% marginal effect), product innovation (1.2%) and patent realization (1.8%). These results seem to be driven by manufacturing firms; for service firms, γ is conversely positive and statistically significant for process innovation (2.9%) and general innovation (3.5%). Observe that in the case of the patent outcome, interacting γ with the macro-sector categories results in very imprecise estimates. In short, these results indicate that the innovativeness of Science Cities seems to somehow spill over the firms that are located sufficiently close to them. While these marginal effects cannot be interpreted in a causal sense, they are indicative of some economic mechanisms that induce firms with more innovation potential to locate in the proximity of Science Cities. These mechanisms operate more in terms of product or process innovation whether firms belong to the manufacturing or the services sector.

For the two agglomeration measures based on the graduate and postgraduate share, the results are qualitatively similar. For the sake of brevity we mainly discuss the former; note that the marginal effects reported next are those associated with an increase of the graduate share of cities s by 1 percentage point. The estimates of γ for the manufacturing sector are positive and statistically significant for the R&D outcome (1.6%), product innovation (1.6%) and the patent outcome (1.9%), but negative and statistically significant for process innovation (−2.1%). Because the results take opposite signs for product and process innovation, the estimate of γ for general innovation is unsurprisingly not statistically significant. However, no relevant correlations are attested for service firms, which explains the small precision of the undifferentiated estimates of γ. The results for the postgraduate share agglomeration measure are very similar to those based on the graduate share; note that the apparently large marginal effects are easily explained in light of the smaller empirical support of the postgraduate share variable.

Like the case of the patent-based agglomeration measure, our estimates based on the relative level of education of those Science Cities that are closer to firms hint at the presence of spillover effects favoring for the most part the manufacturing sector; however, we find the negative and statistically significant estimate for process innovation puzzling. To explain it we hypothesize that manufacturing firms with production technologies closer to the frontier, which consequently are likely to innovate their processes more slowly than those in course of catching up, tend to be located on average closer to Science Cities; the result in question might then be a mechanical artifact of the data.

Finally, observe that our estimates of γ are very imprecise and often not in line with the results previously illustrated, when all three agglomeration measures are included in the estimation (possibly interacted with the macro-sector dummies). This is arguably a result of the fact that the three measures are quite collinear (see Table 4).

7.2 Estimates of $\tilde{\gamma}$: Performance Indicators

The measurement of the returns to R&D and innovation corresponds with a traditional line of research in empirical studies of innovation economics.[32] In our setting, we are similarly interested into uncovering some ultimate performance advantages for firms that locate close to Science Cities, which can be either due to the indirect effect of firm-level innovation spurred by Science Cities (which we illustrated above) or to spillovers of a different kind. To this end, we provide reduced form evidence about the association between Science Cities and firms' labor productivity or sales, by estimating model (12) under different specifications. The results are reported in Table 11; note that for both labor productivity and sales we utilize two different outcome measures, one from our BEEPS survey and the other from Orbis' matched accounting data.[33]

In the case of the patent-based agglomeration measure, $\tilde{\gamma}$ is estimated positive and statistically significant, but only in the case of our BEEPS indicators. By interacting our main regressor G_{fr} with macro-sector dummies, we can observe that this effect appears to operate only among service firms. In our running scenario of a firm located right in the center of a semi-isolated Science City s, one extra fractional patent appears to be correlated with a 14% increase in total sales, and a 12% increase in labor productivity. These are large and relevant figures, although in reality few firms in our sample are that close to Science Cities, and the actual correlation must thus be discounted for distance decay. When estimating the model employing our agglomeration measure based on the graduate-share, we obtain statistically significant results only for our Orbis indicators. Once again, the effects appear to be entirely driven by service firms: if the graduate share increases by one percentage point in the Science City of our reference firm, operating revenue goes up by 4.6%, while labor productivity increases by 4.8%. We obtain qualitatively similar results when using the postgraduate share measure, and when pooling all measures together in our estimates (in this case, $\tilde{\gamma}$ is statistically significant only for service firms when using BEEPS, not Orbis indicators).

[32] See e.g. two relevant surveys: Hall, Mairesse and Mohnen (2010) and Syverson (2011).

[33] Specifically, we employ the measure of *operating revenue* from Orbis.

These results raise two questions. First, one may ask why the results on BEEPS and Orbis indicators do not coincide for each of our agglomeration measures. Clearly, the latter are imperfect measures of the influence of Science Cities; nevertheless, they outline a consistent picture: an association of Science Cities with firm-level performance indicators does exist, but only for service firms. The second question is about the divergence of these results from those about firm-level innovation, which appear to be driven by manufacturing firms instead. To address this interrogative, one must consider the specific context of the Russian transition from a planned to a market economy. In Soviet times the service sector was virtually non-existent, and it has taken decades for it to develop in transitioning Russia to a degree comparable to that of western economies. Manufacturing, on the other hand, underwent a deep restructuring due to the pressure of international competition. It is thus unsurprising that, under favorable conditions, service firms are more easily observed to grow, while manufacturing firms exert more innovative effort. Still, more research – ideally employing longitudinal firm-level data – appears necessary in order to reconcile these different pieces of evidence.

8 Conclusion

In this article we have analyzed the long-run effects of a unique historical placed-based policy: the creation of R&D-focused Science Cities in Soviet Russia. Both the initial establishment and the eventual suspension of this program was largely guided by political factors that are arguably exogenous to drivers of current social and economic conditions of Russian cities. We compare Science Cities to other localities that were observationally similar to them at the time of their selection, and we compute differences in the current characteristics between the two groups. We find that former Science Cities are bigger today, largely because they host a higher number of well-educated individuals. Moreover, they produce a higher number of internationally recognized patents (both in absolute terms and considering the average in the population of potential inventors); their R&D and ICT sectors are more developed, and pay higher salaries; finally, Science Cities host more productive small businesses (although not a higher number of them). Through a separate firm-level analysis, moreover, we attest some evidence in support of the hypothesis that the effect of Science Cities extends beyond their municipal borders.

Because our results hold largely unchanged after the removal, from the estimation sample, of Science Cities that today receive resumed support from the Russian government, we conjecture that they are consequent to the interaction between persistence and agglomeration forces, which we illustrate within a simple spatial equilibrium framework. Specifically, high-skilled individuals who have remained in their former cities of residence have contributed to the emergence of more productive businesses in the new market economy. By analyzing municipal budgets, we rule out alternative explanations such as differential governmental transfers or provision of public goods. In addition, by examining our data in more detail we find little support for rapid mean reversion: thus, we believe that ours is a valuable contribution to the extant literature on place-based policies, which up to now has found only limited evidence in favor of long-run effects following the suspension of a program. More generally, our results are also informative for science and innovation policy, both in the context of emerging economies such as Russia and in those of traditionally capitalistic countries. We hope that these results will be invoked to motivate similar R&D policies but with a civil, instead of military, purpose.

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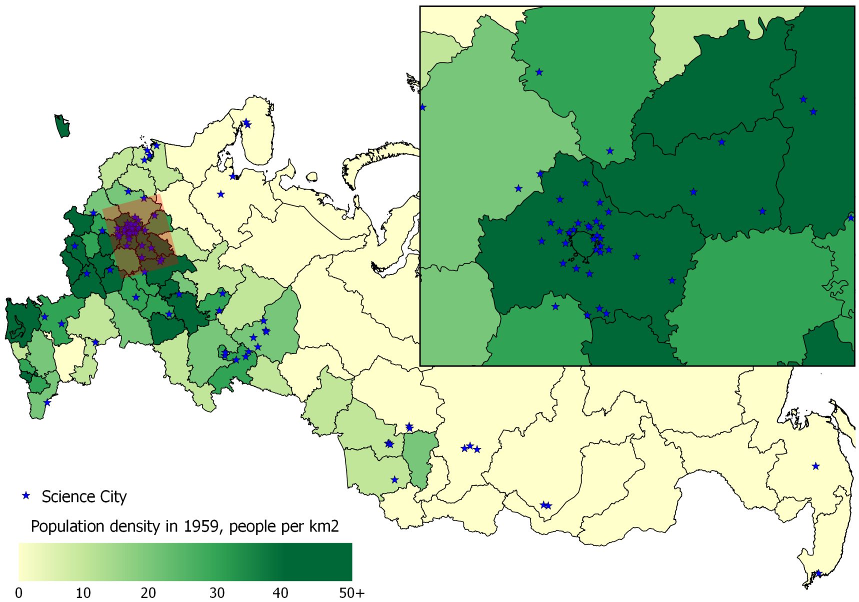
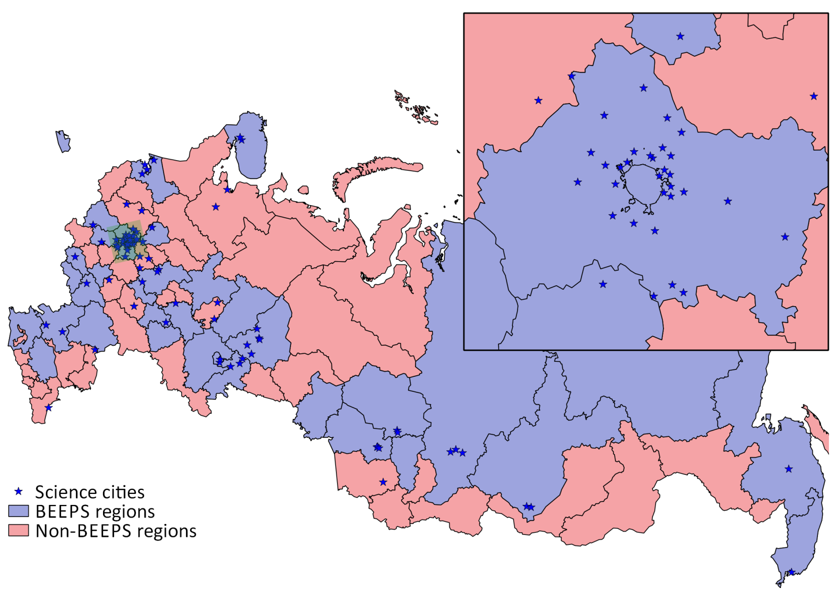
Figures

Figure 1: Location of science cities and regional population density



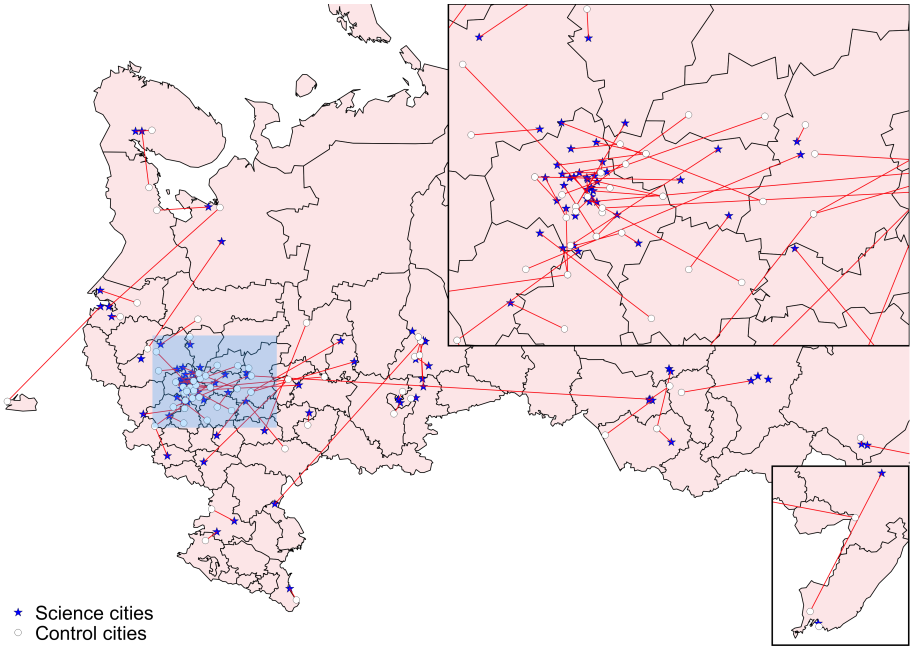
Source: Table A.1 (Data Appendices) and ROSSTAT.

Figure 2: Location of science cities and regions covered in BEEPS V Russia



Source: Table A.1 and BEEPS V Russia.

Figure 3: Science Cities and their matches



Tables

Table 1: Municipal-level data: Descriptive statistics

	Science Cities		Other Municipalities		
	Obs.	Mean (SE)	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 °C	88	-11.632	2250	-13.559	0.000
		(0.410)		(0.149)	
July mean °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 coast	88	0.725	2250	0.730	0.917
		(0.044)		(0.010)	
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)	
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	2.265	0.028	0.000
		(2.944)		(0.107)	
Night lights, 2009-2011	88	30.611	2250	7.638	0.000
		(2.124)		(0.272)	
Avg. Salary in R&D and ICT in 2010 (thousands)	73	24.265	2177	15.368	0.000
		(10.001)		(7.978)	
Employment in R&D and ICT in 2010 (thousands)	73	4.260	2177	1.004	0.026
		(6.937)		(12.394)	
Number of SMEs in 2010 (thousands, all)	69	3239.725	2140	1189.833	0.008
		(742.669)		(67.367)	
SME labor productivity (all)	69	1643.995	2153	794.105	0.000
		(84.513)		(9.213)	
Number of SMEs in 2010 (thousands, manufacturing)	69	395.073	2038	119.546	0.010
		(103.133)		(7.535)	
SME labor productivity (manufacturing)	67	1438.443	2014	768.462	0.000
		(84.554)		(20.805)	

Table 2: Firm-level data: Descriptive statistics

	Obs	Mean	Std. Dev.	Min	Max
Young firms (0-5 years)	4220	0.297	0.457	0	1
50% or more foreign owned	4220	0.026	0.158	0	1
50% or more state owned	4220	0.012	0.108	0	1
Direct exporter	4220	0.100	0.300	0	1
Main market: local	4220	0.697	0.460	0	1
Main market: national	4220	0.288	0.453	0	1
% of employees with a completed university degree	4045	52.505	30.521	0	100
Manufacturing	4220	0.325	0.469	0	1
Located in a city with population over 1 million	4220	0.255	0.436	0	1
Minimum distance of a firm from a Science City (in km)	4220	154.410	237.742	0.198	1358.035
Exponential 1 decay distance of a firm from a Science City	4220	0.012	0.067	0.000	0.822
Log (number of employees), Orbis	2979	3.750	0.860	0.693	8.860
Log (capital), Orbis	3027	5.603	2.089	-2.659	12.916
Log (materials), Orbis	2936	6.212	1.964	-3.912	12.839
Log (operating revenue), Orbis	2980	6.442	1.862	-1.966	13.036
Total factor productivity	2979	0.079	1.356	-8.194	6.544
Log labor productivity, Orbis	2979	2.690	1.343	-5.577	9.167
R&D (dummy)	4220	0.111	0.314	0	1
Technological innovation (dummy)	4220	0.216	0.411	0	1
Product innovation (dummy)	4220	0.129	0.335	0	1
Process innovation (dummy)	4220	0.141	0.348	0	1

Table 3: Agglomeration Variable: Descriptives

	$\lambda = 1$ Mean	Std. dev.	$\lambda = 2$ Mean	Std. dev.	$\lambda = 5$ Mean	Std. dev.
Overall						
Patenting	0.044875	0.564278	0.012969	0.245913	0.008035	0.177558
Higher education	0.000621	0.006970	0.000231	0.003545	0.000154	0.002620
Postgraduate education	0.000018	0.000227	0.000007	0.000116	0.000004	0.000085
Manufacturing						
Patenting	0.016345	0.392833	0.005485	0.198346	0.003667	0.149822
Higher education	0.000256	0.004811	0.000108	0.002680	0.000076	0.002052
Postgraduate education	0.000007	0.000141	0.000003	0.000078	0.000002	0.000059
Services						
Patenting	0.028530	0.406232	0.007484	0.145651	0.004367	0.095458
Higher education	0.000364	0.005062	0.000124	0.002327	0.000078	0.001632
Postgraduate education	0.000011	0.000178	0.000004	0.000087	0.000002	0.000062

Table 4: Agglomeration Variables: Correlations

	$\lambda = 1$ Patenting	Higher education	$\lambda = 2$ Patenting	Higher education	$\lambda = 5$ Patenting	Higher education
Patenting	1		1		1	
Higher education	0.6423***		0.6791***		0.6801***	
Postgraduate education	0.5466***	0.9449***	0.5589***	0.9441***	0.5575***	0.943***

Table 5: Covariate Balance: Mahalanobis Matching, all Science Cities

	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 R&D institutes in 1947	0.7263	0.0523	4.8844	1.1064
(Log) no. of universities in 1959	0.3227	0.0058	3.1266	1.1697
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

Notes: For each variable in the left column, the table reports both the difference in the variance-standardized mean and the variance ratio between treated and control observations, for both the raw sample and the matched sample. The matched sample is obtained through the Mahalanobis matching algorithm applied to the variables above, forcing exact matching on: closed city status, presence of a lake *or* a river in the municipal territory, and direct access to the coast. The number of plants, universities and R&D institutes is increased by one before applying the logarithmic transformation. Matching is one-to-one with replacement.

Table 6: Municipal-level Results: Mahalanobis Matching, all Science Cities

	Whole Sample	*Matched Sample* (1 nearest neighbor)				
Outcome	Raw Difference	T	C	ATT	ATT b.a.	Γ^* ($\alpha = .05$)
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

Notes: * denotes $p < 0.10$, ** denotes $p < 0.05$, and *** denotes $p < 0.01$; where p is the p-value associated to each parameter estimate (standard errors are reported in parentheses). In the matched sample, T is the number of matched treated observations; C is the number of matched controls; 'ATT' and 'ATT b.a.' are two estimates of the ATT respectively excluding and including a bias-adjustment term (Abadie and Imbens, 2011). In both cases, standard errors are computed following Abadie and Imbens (2006). Γ^* is the minimum value of parameter $\Gamma \geq 1$, selected from a grid spaced by intervals of 0.05 length, such that in a sensitivity analysis *à la* Rosenbaum (2002) the set of Wilcoxon signed-rank tests associated with Γ^* do not simultaneously reject the null hypothesis that the outcome variable is not different across the treated and control samples, for tests with $\alpha = .05$ type I error. A higher value of Γ is associated to a stronger simulated unobserved factor which affects both the outcome and the probability of receiving the treatment. Full-fledged results of the sensitivity analysis for specific outcomes are available upon request.

Table 7: Municipal-level Results: Mahalanobis Matching, Historical Science Cities

	Whole Sample	*Matched Sample* (1 nearest neighbor)				
Outcome	Raw Difference	*T*	*C*	ATT	ATT b.a.	Γ^* ($\alpha = .05$)
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

Notes: * denotes $p < 0.10$, ** denotes $p < 0.05$, and *** denotes $p < 0.01$; where p is the p-value associated to each parameter estimate (standard errors are reported in parentheses). In the matched sample, T is the number of matched treated observations; C is the number of matched controls; 'ATT' and 'ATT b.a.' are two estimates of the ATT respectively excluding and including a bias-adjustment term (Abadie and Imbens, 2011). In both cases, standard errors are computed following Abadie and Imbens (2006). Γ^* is the minimum value of parameter $\Gamma \geq 1$, selected from a grid spaced by intervals of 0.05 length, such that in a sensitivity analysis *à la* Rosenbaum (2002) the set of Wilcoxon signed-rank tests associated with Γ^* do not simultaneously reject the null hypothesis that the outcome variable is not different across the treated and control samples, for tests with $\alpha = .05$ type I error. A higher value of Γ is associated to a stronger simulated unobserved factor which affects both the outcome and the probability of receiving the treatment. Full-fledged results of the sensitivity analysis for specific outcomes are available upon request.

Table 8: Municipal-level Results: Mahalanobis Matching, Municipal Budgets Analysis

	Whole Sample	*Matched Sample* (1 nearest neighbor)				
Outcome	Raw Difference	T	C	ATT	ATT b.a.	Γ^* ($\alpha = .05$)
			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

Notes: * denotes $p < 0.10$, ** denotes $p < 0.05$, and *** denotes $p < 0.01$; where p is the p-value associated to each parameter estimate (standard errors are reported in parentheses). In the matched sample, T is the number of matched treated observations; C is the number of matched controls; 'ATT' and 'ATT b.a.' are two estimates of the ATT respectively excluding and including a bias-adjustment term (Abadie and Imbens, 2011). In both cases, standard errors are computed following Abadie and Imbens (2006). Γ^* is the minimum value of parameter $\Gamma \geq 1$, selected from a grid spaced by intervals of 0.05 length, such that in a sensitivity analysis *à la* Rosenbaum (2002) the set of Wilcoxon signed-rank tests associated with Γ^* do not simultaneously reject the null hypothesis that the outcome variable is not different across the treated and control samples, for tests with $\alpha = .05$ type I error. A higher value of Γ is associated to a stronger simulated unobserved factor which affects both the outcome and the probability of receiving the treatment. Full-fledged results of the sensitivity analysis for specific outcomes are available upon request.

Table 9: Municipal-level Results: Mahalanobis Matching, "Dynamic" Analysis

	Whole Sample	*Matched Sample* (1 nearest neighbor)				
Outcome	Raw Difference	T	C	ATT	ATT b.a.	Γ^* ($\alpha = .05$)
All Science Cities						
Graduate Share: born ≤ 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 ≤ 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 ≤ 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 ≤ 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

Notes: * denotes $p < 0.10$, ** denotes $p < 0.05$, and *** denotes $p < 0.01$; where p is the p-value associated to each parameter estimate (standard errors are reported in parentheses). In the matched sample, T is the number of matched treated observations; C is the number of matched controls; 'ATT' and 'ATT b.a.' are two estimates of the ATT respectively excluding and including a bias-adjustment term (Abadie and Imbens, 2011). In both cases, standard errors are computed following Abadie and Imbens (2006). Γ^* is the minimum value of parameter $\Gamma \geq 1$, selected from a grid spaced by intervals of 0.05 length, such that in a sensitivity analysis *à la* Rosenbaum (2002) the set of Wilcoxon signed-rank tests associated with Γ^* do not simultaneously reject the null hypothesis that the outcome variable is not different across the treated and control samples, for tests with $\alpha = .05$ type I error. A higher value of Γ is associated to a stronger simulated unobserved factor which affects both the outcome and the probability of receiving the treatment. Full-fledged results of the sensitivity analysis for specific outcomes are available upon request.

Table 10: Firm-level innovation outcomes: probit average marginal effects ($\lambda = 1$)

Agglomeration potential measure	R&D	Product innovation	Process innovation	Technological innovation	Has a patent
Patenting	0.015***	0.012**	0.005	0.023	0.018***
	(0.003)	(0.005)	(0.009)	(0.016)	(0.006)
Patenting	0.018***	0.014**	-0.015	0.011	0.038
* manufacturing	(0.005)	(0.006)	(0.009)	(0.008)	(0.026)
Patenting	-0.012	0.008	0.029**	0.035**	-0.037
* services	(0.027)	(0.013)	(0.011)	(0.016)	(0.062)
Higher education	0.756	0.698	-0.529	0.519	0.931
	(0.493)	(0.528)	(0.720)	(0.783)	(0.642)
Higher education	1.599***	1.315**	-2.143**	0.964	1.926**
* manufacturing	(0.542)	(0.643)	(0.899)	(0.754)	(0.805)
Higher education	-0.963	-0.210	0.203	0.150	-3.677
* services	(0.964)	(1.042)	(0.904)	(1.270)	(4.954)
Postgraduate education	13.499	12.200	-10.478	9.368	18.536
	(18.595)	(15.758)	(22.860)	(24.771)	(21.692)
Postgraduate education	75.008***	65.665**	-71.526*	45.526	89.147**
* manufacturing	(25.546)	(32.293)	(38.977)	(34.129)	(40.106)
Postgraduate education	-19.784	-19.717	4.273	-0.142	-122.477
* services	(25.008)	(28.159)	(22.892)	(33.250)	(217.412)
Patenting	0.018**	0.011	0.025	0.030	0.024
	(0.007)	(0.009)	(0.017)	(0.020)	(0.015)
Higher education	-0.215	0.963	-7.043*	-2.354	-1.216
	(1.659)	(2.149)	(3.784)	(3.270)	(2.862)
Postgraduate education	-11.507	-35.355	143.479*	32.815	16.247
	(46.695)	(52.332)	(86.155)	(79.706)	(63.918)
Patenting	0.019*	0.011	-0.001	0.012	0.197
* manufacturing	(0.011)	(0.013)	(0.013)	(0.017)	(0.281)
Patenting	0.027	0.076**	0.043***	0.053***	0.002
* services	(0.016)	(0.030)	(0.013)	(0.017)	(0.022)
Higher education	-0.649	-5.44	-4.661**	-2.633	-41.289
* manufacturing	(2.086)	(4.175)	(2.125)	(4.359)	(67.281)
Higher education	-41.438*	185.765	-4.951	-4.490	-8.261
* services	(22.023)	(120.767)	(3.561)	(4.777)	(11.919)
Postgraduate education	18.246	268.314	81.411	114.812	903.725
* manufacturing	(53.436)	(177.391)	(57.724)	(150.719)	(1440.673)
Postgraduate education	946.266*	-9429.358	87.413	62.199	140.698
* services	(519.478)	(6077.819)	(88.581)	(124.558)	(275.909)
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. Patenting 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). Higher education 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: log number of permanent, full-time employees, % of employees with a completed college degree, and indicators for young firms (up to 5 years old), 25% foreign and state ownership, exporter status, local and national main markets for the firms' products, credit constraindness and whether the firm is located in a city with population over 1 million. Linearized Taylor standard errors clustered on strata are reported in parenthesis. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 11: Firm-level performance outcomes: OLS ($\lambda = 1$)

Agglomeration potential measure	Operating revenue (Orbis)	Labor productivity Orbis)	Sales (BEEPS)	Labor productivity (BEEPS)
Patenting	0.009	0.008	0.062**	0.056**
	(0.013)	(0.013)	(0.030)	(0.026)
Patenting	0.001	-0.007	0.010	0.008
* manufacturing	(0.009)	(0.009)	(0.011)	(0.011)
Patenting	0.022	0.028	0.143*	0.126**
* services	(0.025)	(0.024)	(0.074)	(0.052)
Higher education	3.233*	3.267*	0.722	-0.050
	(1.736)	(1.764)	(3.760)	(3.077)
Higher education	0.661	0.668	-1.633	-1.848
* manufacturing	(0.901)	(0.860)	(2.452)	(2.458)
Higher education	4.637**	4.847**	1.700	0.415
* services	(2.127)	(2.020)	(6.031)	(4.856)
Postgraduate education	101.608**	103.101**	-12.015	-31.789
	(51.006)	(51.345)	(111.069)	(92.718)
Postgraduate education	20.363	22.142	-88.690	-94.091
* manufacturing	(20.583)	(20.424)	(75.625)	(75.556)
Postgraduate education	47.301***	151.741***	5.156	-20.325
* services	(39.129)	(36.141)	(145.720)	(121.578)
Patenting	-0.009	-0.009	0.092***	0.093***
	(0.011)	(0.014)	(0.029)	(0.030)
Higher education	0.414	0.312	-3.007	-4.264
	(3.533)	(3.556)	(7.020)	(7.001)
Postgraduate education	97.645	102.369	-41.167	-27.543
	(127.543)	(127.531)	(190.713)	(191.855)
Patenting	-0.002	-0.011	0.050	0.051
* manufacturing	(0.009)	(0.009)	(0.047)	(0.048)
Patenting	-0.002	0.003	0.165***	0.159***
* services	(0.016)	(0.017)	(0.062)	(0.048)
Higher education	-0.117	-0.507	-3.607	-4.052
* manufacturing	(3.066)	(2.614)	(11.677)	(11.830)
Higher education	-0.111	0.342	8.542	4.423
* services	(4.354)	(4.362)	(11.796)	(9.665)
Postgraduate education	24.929	45.430	-78.723	-71.483
* manufacturing	(74.722)	(64.534)	(258.970)	(262.890)
Postgraduate education	152.505	139.483	-339.397	-255.775
* services	(116.684)	(115.726)	(287.565)	(258.725)
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). Orbis measures are based on firm-level data from Bureau Van Dijk's Orbis database, while BEEPS measures are based on firm-level data from BEEPS. Only coefficients on agglomeration potential measures are reported. Patenting 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). Higher education 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: log number of permanent, full-time employees, % of employees with a completed college degree, and indicators for young firms (up to 5 years old), 25% foreign and state ownership, exporter status, local and national main markets for the firms' products, credit constraindness and whether the firm is located in a city with population over 1 million. Orbis measures use information on the number of employees, fixed assets and cost of materials from Orbis; BEEPS measures use information o the number of employees from BEEPS only, as the other measures are not available for non-manufacturing firms. Linearized Taylor standard errors clustered on strata are reported in parenthesis. * significant at 10%; ** significant at 5%; *** significant at 1%.

A.1 Science cities in the Soviet Union and Russia

Table A.1: Science cities

No.	Location[a]	Oblast	Founded[e]	Naukograd: Year Soviet status[e]	Naukograd: Year Russian status[f]	Type[a]	Closed city[d]: Past	Closed city[d]: Now	Priority specialisation areas[a]: Military base	Air rocket and space research	Electronics and radio engineering	Automation, IT and instrumentation	Chemistry, chemical physics and new materials	Nuclear complex	Energetics	Biology, biotechnology and agricultural sciences
1	Biysk	Altai Krai	1718	1957	2005	1	No	No	No	No	No	No	Yes	No	No	Yes
2	Mirny	Arkhangelsk	1957	1966		2	Yes	Yes	No	Yes	No	No	No	No	No	No
3	Severodvinsk	Arkhangelsk	1936	1939		2	Yes	No	Yes	No	No	Yes	No	No	No	No
4	Znamensk	Astrakhan	1948	1962		2	Yes	Yes	Yes	Yes	No	No	No	No	No	No
5	Miass	Chelyabinsk	1773	1955		1	No	No	No	Yes	No	Yes	No	No	No	No
6	Ozyorsk	Chelyabinsk	1945	1945		2	Yes	Yes	No	No	No	No	No	Yes	No	No
7	Snezhinsk	Chelyabinsk	1957	1957		2	Yes	Yes	No	No	No	No	No	Yes	No	No
8	Tryokhgorny	Chelyabinsk	1952	1952		2	Yes	Yes	No	No	No	Yes	No	Yes	No	No
9	Ust-Katav	Chelyabinsk	1758	1942		1	No	No	No	Yes	No	Yes	No	No	No	No
10	Kaspiysk[c]	Dagestan	1932	1936		2	No	No	No	No	No	Yes	No	No	No	No
11	Akademgorodok	Irkutsk	1949	1988		5	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
12	Angarsk[c]	Irkutsk	1948	1957		2	No	No	No	No	No	No	Yes	Yes	No	No
13	Obninsk	Kaluga	1946	1946	2000	2	No	No	No	No	No	Yes	No	Yes	Yes	No
14	Sosensky[c]	Kaluga	1952	1973		3	No	No	No	No	No	Yes	No	No	No	No
15	Komsomolsk-on-Amur	Khabarovsk	1932	1934		1	No	No	No	Yes	No	Yes	No	No	No	No
16	Krasnodar-59[b]	Krasnodar					No	No		No	No	No	No	No	No	No

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[b] Based on NAS (2002).

[c] Based on Lappo and Polyan (2008).

[d] Russian Wikipedia article on closed cities (ZATO), 28 September 2016.

[e] Wikipedia articles for each city, 28 September 2016.

[f] Russian Wikipedia article on science cities, 28 September 2016.

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				Naukograd			Closed city[d]		Priority specialisation areas[a]							
No.	**Location[a]**	**Oblast**	**Founded[e]**	**Year Soviet status[e]**	**Year Russian status[f]**	**Type[a]**	**Past**	**Now**	**Military base**	**Air rocket and space research**	**Electronics and radio engineering**	**Automation, IT and instrumentation**	**Chemistry, chemical physics and new materials**	**Nuclear complex**	**Energetics**	**Biology, biotechnology and agricultural sciences**
17	Akademgorodok	Krasnoyarsk	1944	1965		5	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
18	Zelenogorsk	Krasnoyarsk	1956	1956		2	Yes	Yes	No	No	No	No	Yes	Yes	No	No
19	Zheleznogorsk	Krasnoyarsk	1950	1954		2	Yes	Yes	No	Yes	No	No	No	Yes	No	No
20	Kurchatov[c]	Kursk	1968	1976		2	No	No	No	No	No	No	No	Yes	Yes	No
21	Gatchina	Leningrad	1928	1956		1	No	No	No	No	No	Yes	No	Yes	No	No
22	Primorsk	Leningrad	1268	1948		1	No	No	No	Yes	No	No	No	No	No	No
23	Sosnovy Bor	Leningrad	1958	1962		3	Yes	Yes	No	No	Yes	No	No	Yes	Yes	No
24	Zelenograd	Moscow City	1958	1958		2	No	No	No	No	Yes	Yes	No	No	No	No
25	Avtopoligon	Moscow Oblast	1964	1964		4	No	No	No	No	No	Yes	No	No	No	No
26	Balashikha	Moscow Oblast	1830	1942		1	No	No	No	Yes	No	Yes	No	No	No	No
27	Beloozersky	Moscow Oblast	1961	1961		4	No	No	No	Yes	No	No	No	No	No	No
28	Chernogolovka	Moscow Oblast	1710	1956	2008	3	No	No	No	No	No	Yes	Yes	No	No	No
29	Dolgoprudny	Moscow Oblast	1931	1951		2	No	No	No	No	No	Yes	Yes	No	No	No
30	Dubna	Moscow Oblast	1956	1956	2001	2	No	No	No	Yes	No	Yes	No	Yes	No	No
31	Dzerzhinsky	Moscow Oblast	1938	1956		3	No	No	No	Yes	No	Yes	Yes	No	No	No
32	Fryazino	Moscow Oblast	1584	1953	2003	3	No	No	No	Yes	Yes	Yes	No	No	No	No
33	Istra	Moscow Oblast	1589	1946		1	No	No	No	Yes	No	Yes	No	No	Yes	No
34	Khimki	Moscow Oblast	1850	1950		1	No	No	No	Yes	No	Yes	No	No	No	No
35	Klimovsk	Moscow Oblast	1882	1940		1	No	No	No	No	No	Yes	No	No	No	No

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[b] Based on NAS (2002).

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No.	Location[a]	Oblast	Founded[e]	Naukograd: Year Soviet status[e]	Year Russian status[f]	Type[a]	Closed city[d]: Past	Now	Priority specialisation areas[a]: Military base	Air rocket and space research	Electronics and radio engineering	Automation, IT and instrumentation	Chemistry, chemical physics and new materials	Nuclear complex	Energetics	Biology, biotechnology and agricultural sciences
36	Korolyov	Moscow Oblast	1938	1946	2001	1	No	No	No	Yes	No	Yes	Yes	No	No	No
37	Krasnoarmeysk	Moscow Oblast	1928	1934		1	No	No	No	No	No	Yes	Yes	No	No	No
38	Krasnogorsk[c]	Moscow Oblast	1932	1942		3	No	No	No	No	Yes	No	No	No	No	No
39	Krasnoznamensk	Moscow Oblast	1950	1950		2	Yes	Yes	No	Yes	No	No	No	No	No	No
40	Lukhovitsy	Moscow Oblast	1594	1957?		1	No	No	No	Yes	No	No	No	No	No	No
41	Lytkarino	Moscow Oblast	1939	1957		1	No	No	No	Yes	No	Yes	No	No	No	No
42	Lyubertsi[c]	Moscow Oblast	1623	1948		1	No	No	No	No	No	Yes	No	No	No	No
43	Mendeleyevo	Moscow Oblast	1957	1965		4	No	No	No	No	No	Yes	No	No	No	No
44	Mytishchi[c]	Moscow Oblast	1460	1935		1	No	No	No	No	No	Yes	No	No	No	No
45	Obolensk	Moscow Oblast	1975	1975		4	Yes	No	No	No	No	No	No	No	No	Yes
46	Orevo	Moscow Oblast	1954	1954		4	No	No	No	Yes	No	No	No	No	No	No
47	Peresvet	Moscow Oblast	1948	1948		2	No	No	No	Yes	No	No	No	No	No	No
48	Protvino	Moscow Oblast	1960	1960	2008	3	Yes	No	No	No	No	Yes	No	Yes	No	No
49	Pushchino	Moscow Oblast	1956	1966	2005	3	No	No	No	No	No	No	No	No	No	Yes
50	Remmash	Moscow Oblast	1957	1957		4	No	No	No	Yes	No	No	No	No	No	No
51	Reutov	Moscow Oblast	1492-1495	1940	2003	1	No	No	No	Yes	No	Yes	No	No	No	No
52	Tomilino	Moscow Oblast	1894	1961		4	No	No	No	Yes	No	Yes	No	No	No	No
53	Troitsk	Moscow Oblast	1617	1977	2007	3	No	No	No	No	No	Yes	No	Yes	No	No
54	Yubileyny	Moscow Oblast	1939	1950		3	Yes	No	No	Yes	No	No	No	No	No	No

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No.	Location[a]	Oblast	Founded[e]	Naukograd: Year Soviet status[e]	Naukograd: Year Russian status[f]	Naukograd: Type[a]	Closed city[d]: Past	Closed city[d]: Now	Priority specialisation areas[a]: Military base	Air rocket and space research	Electronics and radio engineering	Automation, IT and instrumentation	Chemistry, chemical physics and new materials	Nuclear complex	Energetics	Biology, biotechnology and agricultural sciences
55	Zheleznodorozhny	Moscow Oblast	1861	1952		3	No	No	No	No	No	Yes	No	No	No	No
56	Zhukovsky	Moscow Oblast	1933	1947	2007	2	No	No	No	Yes	No	No	No	No	No	No
57	Zvyozdny gorodok	Moscow Oblast	1960	1960		4	Yes	Yes	No	Yes	No	No	No	No	No	No
58	Apatity (Akademgorodok)	Murmansk	1926	1954		2	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
59	Polyarnye Zori[c]	Murmansk	1968	1973		2	No	No	No	No	No	No	No	Yes	Yes	No
60	Balakhna (Pravdinsk)	Nizhny Novgorod	1932	1941		1	No	No	No	No	Yes	No	No	No	No	No
61	Dzerzhinsk	Nizhny Novgorod	1606	1930		2	No	No	No	No	No	No	Yes	No	No	No
62	Sarov	Nizhny Novgorod	1310	1947		1	Yes	Yes	No	No	No	No	No	Yes	No	No
63	Akademgorodok	Novosibirsk	1957	1957		5	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
64	Koltsovo	Novosibirsk	1979	1979	2003	4	Yes	No	No	No	No	No	No	No	No	Yes
65	Krasnoobsk	Novosibirsk	1970	1978		4	No	No	No	No	No	No	No	No	No	Yes
66	Novosibirsk-49[b]	Novosibirsk					No	No		No	No	No	No	No	No	No
67	Omsk-5[b]	Omsk					No	No								
68	Zarechny	Penza	1954	1958		2	Yes	Yes	No	No	No	No	No	Yes	Yes	No
69	Perm-6[b]	Perm					No	No								
70	Bolshoy Kamen[c]	Primorsk Krai	1947	1954		2	Yes	Yes	No	No	No	Yes	No	No	No	No
71	Volgodonsk[c]	Rostov	1950	1976		3	No	No	No	No	No	No	No	Yes	Yes	No
72	Zernograd	Rostov	1929	1935		1	No	No	Yes	No	No	No	No	No	No	Yes
73	Petergof	Saint Petersburg	1711	1960	2005	1	No	No	No	No	No	Yes	Yes	No	No	No

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No.	Location[a]	Oblast	Founded[e]	Naukograd: Year Soviet status[e]	Naukograd: Year Russian status[f]	Type[a]	Closed city[d]: Past	Closed city[d]: Now	Priority specialisation areas[a]: Military base	Air rocket and space research	Electronics and radio engineering	Automation, IT and instrumentation	Chemistry, chemical physics and new materials	Nuclear complex	Energetics	Biology, biotechnology and agricultural sciences
74	Desnogorsk[c]	Smolensk	1974	1982		2	No	No	No	No	No	No	No	Yes	Yes	No
75	Lesnoy	Sverdlovsk	1947	1954		2	Yes	Yes	No	No	No	No	No	Yes	No	No
76	Nizhnyaya Salda	Sverdlovsk	1760	1958		1	No	No	No	Yes	No	No	No	No	No	No
77	Novouralsk	Sverdlovsk	1941	1949		2	Yes	Yes	No	No	No	No	Yes	Yes	No	No
78	Verhnyaya Salda[c]	Sverdlovsk	1778	1933		3	No	No	No	No	No	No	Yes	No	No	No
79	Zarechny	Sverdlovsk	1955	1955		2	No	No	No	No	No	No	No	Yes	Yes	No
80	Michurinsk	Tambov	1635	1932	2003	1	No	No	No	No	No	Yes	No	No	No	Yes
81	Zelenodolsk[c]	Tatarstan	1865	1949		1	No	No	No	No	No	Yes	No	No	No	No
82	Akademgorodok	Tomsk	1972	1972		5	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
83	Seversk	Tomsk	1949	1949		2	Yes	Yes	No	No	No	No	Yes	Yes	No	No
84	Redkino	Tver	1843	1950		4	No	No	No	No	Yes	No	Yes	No	No	No
85	Solnechny	Tver	1947	1951		4	Yes	Yes	Yes	No	No	Yes	No	No	No	No
86	Udomlya[c]	Tver	1478	1984		3	No	No	No	No	No	No	No	Yes	Yes	No
87	Glazov[c]	Udmurtia	1678	1948		1	No	No	No	No	No	No	No	Yes	No	No
88	Votkinsk[c]	Udmurtia	1759	1957		1	No	No	No	Yes	No	Yes	No	No	No	No
89	Dimitrovgrad	Ulyanovsk	1698	1956		1	No	No	No	No	No	No	No	Yes	Yes	No
90	Kovrov	Vladimir	1778	1916		1	No	No	No	No	No	Yes	No	No	No	No
91	Melenki	Vladimir	1778			1	No	No	No	No	No	Yes	No	No	No	No
92	Raduzhny	Vladimir	1971	1971		2	Yes	Yes	No	No	Yes	Yes	No	No	No	No

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				Naukograd			Closed city[d]		Priority specialisation areas[a]							
No.	Location[a]	Oblast	Founded[e]	Year Soviet status[e]	Year Russian status[f]	Type[a]	Past	Now	Military base	Air rocket and space research	Electronics and radio engineering	Automation, IT and instrumentation	Chemistry, chemical physics and new materials	Nuclear complex	Energetics	Biology, biotechnology and agricultural sciences
93	Novovoronezh[c]	Voronezh	1957	1964		2	No	No	No	No	No	No	No	Yes	Yes	No
94	Borok	Yaroslavl	1807	1956		4	No	No	No	No	No	No	No	No	No	Yes
95	Pereslavl-Zalessky	Yaroslavl	1152	1964		1	No	No	No	No	No	Yes	Yes	No	No	No

[a] Based on Aguirrechu (2009), unless specified otherwise. Type: 1 - science cities, "scientific core" established in existing cities, which often had a particular historical significance; 2 - science cities that received city status simultaneously (or a few years later) with the creation of a scientific or scientific-industrial complex at a practically new location (often in the "open field"); 3 - science cities that have arisen in existing settlements and received city status after obtaining scientific functions; 4 - science cities that do not have city status; 5 - academic town.

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A.2 Municipal level data sources and variables

Table A.2: Municipal level data sources and variables

Data type	Data sub-type	Data source	Description
		Factors guiding the selection of location of science cities	
Administrative	Various identification information for municipality, region and federal district	OpenStreetMaps, available through GIS-LAB (`http://gis-lab.info/qa/osm-adm.html`)	Unique municipality, federal district and region (oblast, krai, republic) identificators, codes and names
Population	1959 census data	January 1959 Soviet Census, available through Demoscope (`http://demoscope.ru/weekly/ssp/census.php?cy=3`)	All population in municipality in 1959, estimates for some municipalities
Geography	Area	Calculated in QGIS based on OpenStreetMaps	Municipality area calculated in QGIS, measured in squared kilometers
	Coordinates of the municipality center		GPS coordinates of the center of municipality calculated in QGIS
	Altitude	CGIAR.[a] Consortium for Spatial Information (CGIAR-CSI) SRTM 90m Digital Elevation Data, version 4, available at `http://srtm.csi.cgiar.org/`	Altitude of municipality in meters (mean, median, SD, min and max value)
	Temperatures in January and July	WorldClim version 1 (`http://www.worldclim.org/version1`), developed by Hijmans et al. (2005)	Monthly temperature data, for the period 1960-1990, assigned to municipalities in QGIS. Average, median, standard deviation, minimum, and maximum.

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Data type	Data sub-type	Data source	Description
	Railroad	Vernadsky State Geological Museum and U.S. Geological Survey, 20010600 (2001) and Central management unit of the military communications of the Red Army (1943)	Data on railroads were constructed using railroads shapefile describing the railroads of the former Soviet Union as of the early 1990s prepared by Vernadsky State Geological Museum and U.S. Geological Survey, 20010600 (2001), along with a map of railroads from 1943 from Central management unit of the military communications of the Red Army (1943) to manually remove any differences between the situation depicted in the shapefile and the 1943 map. Indicator equal to 1 if municipality has access to railroad, and 0 otherwise. Railroads are as of late 1940s.
	Coastline/major river/lake	Natural Earth, 1:10m Physical Vectors version (`http://www.naturalearthdata.com/downloads/10m-physical-vectors/`)	Indicator equal to 1 if municipality has access to coast/major river/lake and 0 otherwise.
	Distances	Calculated in QGIS based on the sources specified above	Distance (in km) from the centre of municipality to the nearest railroad, coast, major river, lake, USSR border, plant (of any type), and HEI (of any type).
Level of industrial development	Data on the factories, research and design establishments of the Soviet defense industry in 1947	Dexter and Rodionov (2016). The dataset contains ~30,000 entries and includes the name, location, main operation, type of establishment as well as the start and end date for the establishment's military work.	Number of factories (*zavod*) and subordinated organizations
R&D institutes			Number of Scientific Research & Design Institutes (*NII*, *TsNII*, and *GSPI*), design bureaus, and test sites
Higher education institutes (HEI)	HEIs in the municipality in 1959	De Witt (1961)	Number of all HEIs, HEIs specializing in technical sciences, and HEIs specializing in biology and medical sciences
State bank branches	State bank branches as of 1946	Bircan and De Haas (2017), originally from the USSR State Bank's archival documents	Number of branches of the USSR State Bank.

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Data type	Data sub-type	Data source	Description
		Long-term outcomes of interest	
Patents	Applications to EPO	European Patent Office. Patents are matched to municipalities via inventors' addresses.	Number of patents applications to EPO in 2006-2015, by inventor (simple and fractional counting)
	Granted patents		Number of patents granted since 2006 (simple and fractional counting)
Population	2010 census data	2010 Russian Census, available at `http://www.gks.ru/free_doc/new_site/perepis2010/croc/perepis_itogi1612.htm`	All population, population with higher education, and population with PhD or doctoral degrees in municipality in 2010
Nighttime lights	Average stable nightlights	Version 4 DMSP-OLS Nighttime Lights Time Series, National Oceanic and Atmospheric Administration (NOAA) (`http://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html`)	Average nightlights for 1992-1994 and 2009-2011, cleaned of gas flares
SMEs	Results of the 2010 SME census	Rosstat (Federal State Statistics Service) (`http://www.gks.ru/free_doc/new_site/business/prom/small_business/itog-spn.html`)	The dataset contains information on the number of firms, revenue, number of employees, fixed assets, and fixed capital investment by size, 1- and 4-digit ISIC sector. We use SMEs per capita, SME sales per worker (Labor productivity), and SME sales per unit of fixed Labor, all sectors and manufacturing only. The SME census does not cover ZATOs, so 16 science cities, which are also ZATOs, are not covered.
Municipal budget	Average municip. budget revenues and expenditures over 2006-2016	Rosstat (Federal State Statistics Service)	Average annual municipal budget revenues and expenditures over 2006-2016, in 2010 prices. Total values and breakdown by major categories.

[a] CGIAR is a global partnership of research organizations dedicated to reducing poverty and hunger, improving human health and nutrition, and enhancing ecosystem resilience through agricultural research. CGIAR-CSI is spatial science community that facilitates CGIAR's international agricultural development research using spatial analysis, GIS, and remote sensing: `http://www.cgiar-csi.org/`.