Technology Diffusion through Cultural Links: Evidence from Industrial Firms in Late Imperial Russia*

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Abstract

This paper examines the impact of ethnic connections on the diffusion of technology in a late-industrializing economy. Using machine learning, we assigned probable ethnicities to nearly 16,000 industrial firm owners in the Russian Empire in 1894. We then compared firms owned by entrepreneurs with cultural connections to Europe (e.g., Germans and Poles) to Russian-owned firms. "Connected" firms exhibited higher productivity, employed modern machinery and advanced management practices. We provide evidence for possible mechanisms, like knowledge diffusion, by showing that "connected" firms traded more with Europe, and that German-origin entrepreneurs had the largest productivity advantage in chemicals – Germany's leading industry at the time. Our findings highlight the importance of cultural links in the diffusion of the Industrial Enlightenment from the industrial core of Europe to its periphery.

Keywords: technology diffusion, culture, Industrial Enlightenment, Russian Empire

JEL codes: N33, N43, N53, J47, O43

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1 Introduction

What factors facilitate the adoption of industrial technologies in developing economies? The existing empirical research has primarily examined macro-level cross-country diffusion patterns[1] or studied the adoption of specific technologies in individual industries.[2] In this paper, we take an economy-wide micro-level approach exploring the universe of manufacturing firms in the Russian Empire, which is a typical example of a late-industrializing economy. We show that firm owners' cultural connections with Western Europe, manifested by their ethnic origin, facilitate the adoption of advanced technologies, both at extensive and intensive margins, and increase firm productivity.

We employ the uniquely detailed and comprehensive manufacturing census of about 16,000 private industrial firms conducted by the Ministry of Finance of the Russian Empire in 1894.[3] The census contains information on a firm's name, location, industry, employees, machinery, revenue, and other variables. Crucially, it includes the owners' surname, which allows us to identify the likely ethnicity of a firm owner. We employ a combination of automated approaches and a supervised machine learning algorithm to classify them into one of five different groups, namely Russians, Germans, Jews, Other Westerners (Poles, Lithuanians, etc.), and Eastern minorities (Tatars, Armenians, etc.). Of these five groups, we consider Germans, Jews, and Other Westerners culturally "connected" to Europe, while Russians and Eastern minorities as "non-connected".

We find that "connected" firms were significantly more productive and adopted more advanced industrial machinery and advanced management practices in the early stages of Russian industrialization. In particular, firms owned by "connected" entrepreneurs were more productive in terms of revenue per worker and TFP, more likely to employ machinery instead of draft animals or human labor alone, and more likely to employ machinery with greater horsepower that ran on modern types of fuel such as oil or gas. They also adopted advanced management practices by sharing ownership with partners and operating more regularly throughout the year. Using the decomposition proposed by Gelbach (2016), we find that observed differences in capital and, mostly, management practices account for roughly one quarter of the revenue-per-worker gap and one sixth of the TFP gap, leaving most of the productivity premium unexplained by

[1] See Comin and Mestieri (2014) for the literature review.

[2] See Caselli and Coleman (2001) on the diffusion of personal computers, Manuelli and Seshadri (2014) on the diffusion of tractors, and Foster and Rosenzweig (2010) for the review of micro-level evidence; Griliches (1957) is the seminal paper on the topic.

[3] See Gregg (2020) for the first paper based on this census and Gregg (2026) for a detailed data description.

these measured characteristics. This suggests that some other, unobserved characteristics of factory operation drove the productivity differences. Focusing on private firms instead of corporations ensures that these advantages did not originate from access to stock market, protection of limited liability, or other exclusive legal rights.

We conjecture that one of the possible reasons for the higher productivity of "connected" entrepreneurs was their knowledge of modern production techniques acquired through cultural links with European countries. Unfortunately, the manufacturing census does not contain information on a firm's trade or investment activities, which would allow us to directly test this conjecture. Instead, we develop several alternative approaches using additional data sources.

First, we digitize data for all Russian firms that participated in the 1893 Chicago World Fair, which was an international exhibition of the technological advances of leading industrial nations in the late 19th century. We find that, even among these positively selected firms, the owner's ethnic origin predicts the extent of their commercial ties to Western Europe. "Connected" firms were significantly more likely to trade with European countries.

Second, we identify the industries in which Germany, one of the leading industrial nations at the time, had a comparative advantage, and see whether entrepreneurs of German origin in the Russian Empire also had an advantage in the same industries. We find that firms with owners of German origin had the largest productivity advantage in the chemical industry with about 100% higher revenue per worker than Russian- and Eastern Minority-owned firms. This directly corresponded to Germany's world ascendance in the chemical industry in the late 19th century. Other connected groups had no such advantage. Moreover, we do not observe any "German premium" for industries in which Germany had no comparative advantage at the time, such as cotton textiles, wool- and silk-making.

Third, we digitize a separate data set on patents issued in the Russian Empire in 1892-1896. We find that of all patents issued to the citizens of the Empire, about 75% had been granted to individuals with western surnames and only 24% to individuals of Russian or Eastern minorities origin. Thus, even domestic innovation in the Russian Empire appears to have been largely driven by the "connected" groups.

Finally, ease of communication and transportation to Europe could play a role in facilitating cultural connections. We find that the "connected" groups benefited more than the "non-connected"

ones from locating in one of the 17 largest cities with population exceeding 100,000. The cities provided communication channels necessary to maintain connections with Europe. Furthermore, we find little evidence that "connected" firms closer to the European border benefited from the shortened physical distance itself.

Since our exercises are descriptive in nature, we provide additional evidence to test for possible competing explanations. One of those is initial investment: firm owners with European surnames may have started their businesses with significantly larger capital. We address this concern showing that the productivity premium for "connected" firms existed even within the sub-sample of firms without any machinery, namely without significant initial capital investments. We further show that the premium persisted both in districts with very high average literacy and in majority-Russian districts. These findings alleviate concerns that the results are driven by differences in human capital between "connected" and "non-connected" entrepreneurs or by in-group biases in more ethnically diverse districts.

In addition, we show that the productivity premium for "connected" firms could not be explained by ethnic network effects: being surrounded by upstream and downstream firms owned by individuals of the same ethnicity does not increase firm productivity and, if anything, is associated with lower performance.

This paper contributes to two strands of literature. First, we contribute to the literature on cultural determinants of technology diffusion. Spolaore and Wacziarg (2009) show that cultural barriers, measured by the genetic distance to the technological frontier, explain a large portion of the productivity gap in a cross-section of countries today. Historically, the diffusion of the Industrial Enlightenment (Mokyr, 2016) across Europe was associated with higher levels of upper-tail human capital (Squicciarini and Voigtländer, 2015), presence of scientific societies (Cinnirella et al., 2025), migration of skilled minorities (Hornung, 2014) and creative individuals (Serafinelli and Tabellini, 2022). Our paper shows that, in addition to the aforementioned factors, cultural connections via ethnic links facilitate technology diffusion even without migrations, and may compensate, to some extent, for rigid institutions and insufficient human capital in a receiving country.

Second, we contribute to the growing empirical literature on the industrialization of the Russian Empire viewed from a micro-level perspective. Gregg (2020) demonstrates a strong association between corporate form and productivity; and Gregg and Nafziger (2019, 2024) show that Rus-

sian corporations demonstrated dynamism and flexible financial strategies despite operating in a rigid institutional environment; Gregg and Matiashvili (2022) show the role of factory operating time with respect to industrialization and growth. We show that cultural and ethnic origin of a firm owner played an important role in operating decisions, such as capital investments, working days and organizational form, which contributed to industrialization prior to 1914.

2 Historical background

The Russian Empire at the end of the 19th century was a multicultural and multiethnic society. According to the 1897 population census, those who listed Russian as their first language did not constitute a majority of the empire (44.3%). A significant proportion of the population was made up of ethnic groups with connections to other European countries: Polish, Jewish (Hebrew, Yiddish, other), and German language speakers (6.31%, 4.03%, and 1.43% respectively).

At the same time, the Russian Empire in the late 19th century was a sprawling and institutionally rigid polity undergoing a slow and uneven transition toward industrialization. While industrial output grew rapidly during this period, especially in textiles, mining, and metallurgy, the Empire remained behind Western Europe in terms of productivity, technological complexity, and infrastructure (Gerschenkron, 1962). The state played an active role in promoting industrialization, culminating in the ambitious economic policies of Minister of Finance Sergey Witte in the 1890s. The Ministry of Finance led efforts to systematically collect data on the country's manufacturing performance, resulting in the 1894 census of industrial establishments, which was one of the most detailed firm-level industrial surveys conducted in a relatively lagging country during the 19th century (Ministry of Finance, 1897).

In the late 19th and early 20th centuries, the Russian Empire also experienced a significant influx of foreign entrepreneurship. McKay (1970) shows that foreign investment in Russian industrial corporations surged from 17% in 1880 to 47% by 1914. In the critical industries of steel production and coal mining, foreign entrepreneurs introduced advanced technologies that significantly outpaced those used by local firms. For example, Belgian and French coal mining firms and German metallurgical companies adopted continuous production processes, vertical integration, and the latest coking and smelting technologies. These innovations allowed them to achieve greater efficiency and scale compared to domestic competitors. These firms did not merely replicate Western techniques; they adapted them to local conditions, facilitating a crucial

technological transfer in a late-industrializing economy.

In addition to technological innovations, foreign entrepreneurs in the Russian Empire also introduced advanced forms of industrial management. Foreign-owned corporations, particularly those from Belgium and France, tended to adopt more modern managerial structures than Russian-owned enterprises, including the delegation of responsibility to professional managers rather than relying solely on owner supervision (McKay, 1970, pp. 158–161). These firms often prioritized technical expertise in hiring decisions and created specialized supervisory roles facilitating more efficient labor management.

This paper seeks to extend insights drawn primarily from observations of foreign-owned corporations to the universe of private, locally owned firms with more limited access to foreign capital. We also focus beyond "business immigrants" by including ethnic minorities who maintained cultural and commercial ties to Europe. By adopting a cross-industry perspective, we assess the pervasiveness of knowledge transfer mechanisms across the economy, rather than confining the analysis to a handful of capital-intensive sectors.

3 Data and measurement

3.1 Data sources

Manufacturing census. Our primary source of data is the 1894 Russian Manufacturing Census, conducted by the Imperial Ministry of Finance and published in 1897 (Ministry of Finance, 1897) originally digitized by Gregg (2020). The census only includes manufacturing firms and excludes mining, farming, fishing and other non-manufacturing industries. Its purpose was to inform the central government about the industrialization of the Empire and the spatial distribution of industrial activities. The census did not inform tax collectors, so the usual concern of underreporting in such surveys does not apply to these data. A factory was included in the census if at least one of the following conditions was met: it had at least 15 employees or had a steam engine, a steam boiler, or other mechanical device. The census includes a large number of variables describing a factory's operation: owners' first and last names, location, types of products the firm produced, number of employees by sex and age groups, number and types of machine, horsepower per machine, total revenue, and others. The total number of firms covered by the census was 17,149. Limiting this sample to private firms results in a dataset of 15,880

firms.

Jewish surnames. We use "A Dictionary of Jewish Surnames from the Russian Empire" by Beider (2008), which includes all last names used by Jews of the Russian Empire, for a total of about 74,000 last names.[4] We use this source to distinguish Jewish last names on the one hand, and Russian or German last names on the other, since many Jewish last names had either Russian or German last name structure (see the following subsection for the ethnicity assigning algorithm).

Chicago World's Columbian Exposition. The Russian Empire presented 1,022 exhibits at the 1893 Chicago World's Columbian Exposition, which included art, inventions, and, notably, factory output and machines. The Ministry of Finance issued a catalog of all Russian exhibits, government- or privately owned (Ministry of Finance, 1893). If an exhibitor represented a factory, a short blurb describing the factory was attached. The blurb usually included the owner's name, founding year, number, type, and machine power of any engines in the factory, number of employees, and export-import operations. We digitize this information for all 262 firms in the catalog. We were able to match 122 of them to the 1894 manufacturing census using the firm's name, location, and industry. The rest of the firms would not have met the census inclusion criteria due to their size or production technology.

Patents. We use patent data to explore the differences in inventive activities between "connected" and "non-connected" ethnic groups. The Russian Empire had been issuing patents since 1812. Similarly to Western Europe and the US, inventors would apply for patents for their inventions, which would receive protection if deemed eligible. The duration of the patent could last from one to ten years, depending on the fee paid by the inventor. We digitize a comprehensive list of all patents issued in the years 1892-1896 from the official source published by the patent office of the Department of Trade and Manufacturing (1897). The list includes the assignee's name, citizenship, the nature of the patent, the year of the grant, and the patent term. While there are very few firm owners from the census that we can match to the patent database, the data provide additional evidence on innovative activity by various ethnic groups.

Population census. We augment the manufacturing census with data from the 1897 population census. The population census, among others, provides information on the share of each ethnic group in a district, allowing us to differentiate the districts by their ethnic labor and customer bases. In addition, we use data on literacy rates to isolate the effect of human capital on firm

[4]We thank the author, Alexander Beider, who kindly shared the data.

productivity.

3.2 Measurement: assigning ethnicities to firms

The primary measurement challenge of our study is to correctly assign 9,705 unique firm owners' surnames to a particular ethnic group. The assignment would enable us to classify owners into two broad categories: 1) "Connected" – ethnic groups with a large number of their representatives in European countries, such as Germans, Jews, and Poles; and 2) "Non-connected" – the rest of the sample, which include ethnic Russians and ethnic minorities of the Empire (Tatars, indigenous people of the Caucasus, etc.). Recognizing that the assignment can never be perfect, we combine several complementary approaches to construct the measure.

First, we use the comprehensive dictionary of all Jewish surnames in the Russian Empire, compiled by Beider (2008), to identify Jewish-owned firms. Separating Jewish surnames from Russian ones is important, since we classify Jews as a "connected" group (having a large diaspora in Europe), and Russians as "non-connected". Further, we would like to separate Jewish and German entrepreneurs, since these groups enjoyed different legal rights in the Russian Empire. This separation is never perfect, since Beider's dictionary contains a number of mixed-use surnames. For example, "Levin" could be a Jewish or a Russian surname, and "Schwartz" could be Jewish or German. However, we believe this does not pose a serious threat to our estimation. By mistakenly classifying some Russian surnames as Jewish, we bias our coefficients of interest downward against our hypothesis. By doing the same with Germans, we are shrinking the German sub-group within the "connected" group. In either case, we are not inflating the coefficient on the "connected" group in our regressions. The matching between the dictionary and the manufacturing census shows that 27% of the unique surnames in the census were Jewish, corresponding to 35% of all firms.[5]

Having separated Jewish surnames, we are left with 7,119 unique non-Jewish surnames. We then use the fact that several ethnic groups in the Empire had characteristic last name endings, e.g., *"-ko"* for Ukrainian, *"-ok"* for Belarussian, *"-shvili"* for Georgian, *"-yan"* for Armenian, etc. We sort them out manually. Next, we sort out Russian-sounding surnames using common surname endings like *-ov(ova), -ev(eva)*, and *-in(ina)*. Within the Russian-sounding category there are at least two subgroups: ancestral Russian surnames and "Russified" surnames, namely

[5] In addition to Beider (2008), we use the Jewish Name Index from Abramitzky et al. (2020) as a second classification method. Results obtained with this source are very similar.

the surnames of ethnic minorities, like Tatars, who changed their surname endings to Russian sounding ones in order to assimilate with the Russian majority. To distinguish between these two groups, two human trainers manually classified a subsample of 500 firms. We then fitted a machine-learning algorithm (logistic regression), which produced high-accuracy results (94%).

The rest of the sample consists of non-Russian-sounding surnames, including German, French, Polish, Baltic peoples', and other European surnames. The goal was then to separate German-sounding surnames. Again, a subsample of 500 firms was manually classified, and the machine-learning algorithm was then applied to the remaining list. Accuracy was realistically high - more than 73%. Having sorted out German surnames, we code the rest of the non-Russian-sounding sub-sample as "Other Connected" groups.

Thus, the whole sample of firms was divided into five mutually exclusive groups: Jewish firms (35%), Russian firms (34%), Other Connected firms (19%), German firms (12%), and Eastern minorities' firms (1%). The remaining 1% (109 firms) had mixed connected ownership (e.g. German and Other Connected). We assign "Other Connected" classification to this group.[6] In the empirical analysis that follows, we first compare the "connected" firms (German, Jewish and Other Connected firms combined) with "non-connected" firms (Russians and Eastern minorities combined). We usually repeat the analysis splitting the "connected" group into German, Jewish, and Other connected firms, and leaving Russians and Eastern minorities combined as a baseline comparison group.

3.3 Descriptive statistics

Table 1 presents summary statistics for the whole sample. Connected firms accounted for about 65% of all firms in the Census, while non-connected accounted for the remaining 35%. An average firm employed about 40 workers, generated about 1,700 rubles of revenue per worker, 46% of firms had at least one machine, and 33% had a steam engine. About 44% were located in urban areas. Machine power was heterogeneous across firms, with a mean (20) and median (0) far apart, particularly due to many firms with no machine power.[7]

[6] An additional challenge in our ethnicity assignment algorithm was the fact that some firms belonged to several individuals with different surnames. In rare cases, one owner would be "connected" while another would be Russian. We code these firms against our main hypothesis, such that all firms with at least one "connected" owner are coded as "connected". Similarly, every firm with no "connected" owner and at least one Russian owner is coded as Russian.

[7] Given the prevalence of zeros, we always use Poisson Pseudo-Maximum-Likelihood estimation in the specifications where machine power is the dependent variable.

Table 1: Summary Statistics

	Mean	Median	Std. dev.	N
Firm ownership				
Connected firms	0.65	1	0.48	10,380
German	0.12	0	0.32	1,890
Jewish	0.35	0	0.48	5,492
Other Connected	0.19	0	0.39	2,998
Non-Connected firms	0.35	0	0.48	5,500
Russian	0.34	0	0.47	5,327
Eastern minorities	0.01	0	0.11	173
Productivity measures				
Revenue per worker, rubles	1743	973	2968	13,645
Revenue TFP	-0.013	0	1.1	13,645
Machine power, horsepower	20	0	76.14	15,880
Has at least one machine, %	46	0	50	15,880
Has at least steam engine %	33	0	47	15,880
Other firm's characteristics				
Number of employees	40.4	14	115.8	15,880
Women employees, %	7.5	0	17	15,880
Age of a firm, years	16.7	11	19.8	15,880
Urban location, %	43.8	0	49.6	15,880
Number of working days	215	240	79.9	15, 609

Notes: Data from the 1894 Manufactures Census of the Russian Empire (Ministry of Finance, 1897). Ethnicity of firm owners assigned according to our algorithm described in Section 3.2. Revenue TFP is derived from a Cobb-Douglas production function by regressing log revenue on log total employment and log total horsepower generated by machines and horses (+1). Machine power and presence of machine power exclude any power generated by animals.

Exploring one firm in detail allows us to understand the data better. A firm called "Solitermann" was a machine-intensive, high revenue-per-worker firm in the census. First, we focus on the firm owner's last name: Solitermann. This suggests that the firm was (1) a single proprietorship, since we do not have multiple last names or a plural of the same last name and (2) was most likely owned by a Jewish entrepreneur. Thus, the firm's name reveals both its legal status and the likely ethnicity of the owner.

"Solitermann" was located in the city of Bratslav in the Podolsk province and operated in the flour production sub-industry within the food processing industry. It had one water wheel, which generated 75 horsepower in energy. It employed 14 workers (no women or children), was founded in 1888, operated for 240 days in 1894, and generated 65,202 rubles in revenue, resulting in 4,657 rubles per worker in revenue. A median firm in the census was somewhat less successful than "Solitermann". It employed 14 people (usually only men) and was slightly more likely to be located in a rural area. It operated in a relatively simple industry, like textiles or food processing, and had no horsepower units from machines. It was open for 240 days a year, suggesting it was most likely closed for the summer agricultural season, and generated 973

rubles per worker in revenue.

In addition to revenue per worker and machine power, we use revenue TFP as our productivity measure. We define revenue TFP as the residual of the simple Cobb-Douglas production function, with log capital (+1) defined as the log of a factory's horsepower[8] and log labor defined as the log of the total number of employees. Here we face a common challenge in industrial literature, where we observe factory-level revenues but not the quantities produced. Thus, our definition of TFP represents revenue (TFPR) rather than output (TFPQ) total factor productivity. While this measure may have flaws due to the underlying heterogeneity in prices, our data only allow us to measure TFPR. Crucially, Hsieh and Klenow (2014) show that TFPR rises with TFPQ, although by less than one-for-one.[9] That is, inasmuch as we find between-factory TFPR differences, these differences may understate true productivity differences based on TFPQ.

Table 2: Firm shares by industries and owner' ethnic origin

	Connected			Not Connected		
	Jewish	German	Other Connected	Russian	Eastern	Total
All industries	0.35	0.12	0.19	0.34	0.01	15880
Food processing	0.32	0.13	0.25	0.30	0.01	6843
Animal products	0.35	0.05	0.08	0.51	0.01	1668
Metals and Machines	0.35	0.17	0.19	0.28	0.01	1387
Mineral extraction	0.35	0.11	0.16	0.37	0.01	1181
Wool	0.44	0.20	0.16	0.20	0.00	1006
Wood	0.37	0.13	0.18	0.30	0.01	947
Paper	0.39	0.13	0.21	0.26	0.02	756
Chemical	0.37	0.10	0.14	0.38	0.02	627
Cotton	0.32	0.07	0.07	0.52	0.03	479
Mixed Materials	0.38	0.13	0.14	0.34	0.01	402
Flax	0.36	0.01	0.05	0.57	0.01	328
Silk	0.26	0.04	0.05	0.53	0.12	256

Notes: Data from the 1894 Manufactures Census of the Russian Empire (Ministry of Finance, 1897). Ethnicity of firm owners assigned according to our algorithm described in Section 3.2.

Table 2 splits the sample by industry and ownership ethnicity. The upper row shows the share of each group in the whole sample. The following rows show the same shares separately for each industry. While Russian firms constituted 34% of all firms, they were over-represented in animal products processing, cotton and flax production, and mineral extraction. German firms accounted for 12% of all firms, they were over-represented in the production of machines and metals, and underrepresented in animal product processing and textiles (cotton, flax and silk production). The most striking observations concern Jewish entrepreneurs. First, they were heavily over-represented in the manufacturing census – while Jews constituted less than 5% of

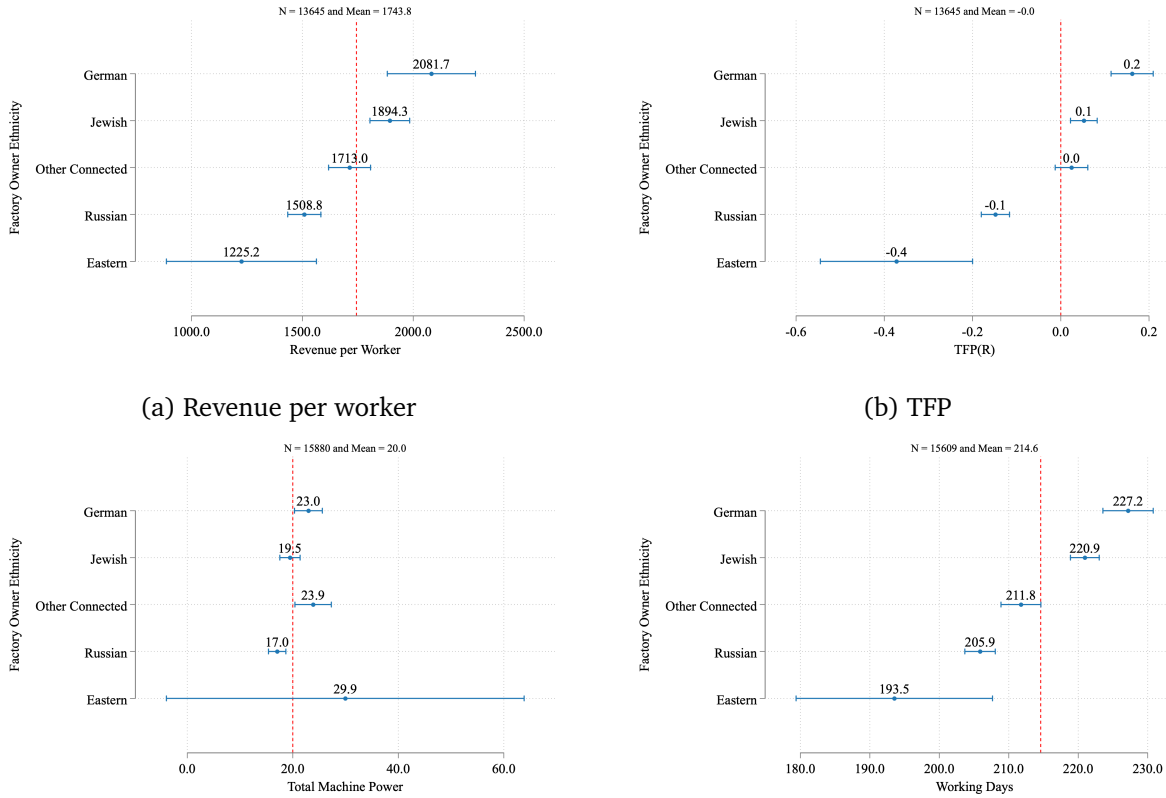
[8]Unlike in the rest of the paper, we use the horsepower generated by both machines and animals to account for all capital when defining TFP.

[9]Between-country variation in how much TFPR responds to rises in TFPQ varies from as low as 10 percent in the US to 50-60 percent in Mexico (Hsieh and Klenow, 2014).

the population in the Russian Empire, they accounted for 35% of industrial firm owners. Second, they had an approximately even presence in all industries, with the share range between 25% and 44% of firms in each industry.

Next, we look at the differences in productivity measures across different ethnic groups. Figure 1 plots firms' characteristics for each of the five groups we identified with our ethnicity assignment algorithm.

We observe that German firms were leaders in terms of revenue per worker, TFP, and the number of working days per year. Jewish firms were significantly higher than average in revenue per worker, TFP, and working days, but not in machine power. Other Connected firms (Polish, Baltic peoples) were higher than average in terms of machine power and close to the average in revenue per worker, TFP, and working days. Russian and Eastern minority firms were below average in all productivity measures and working days per year, although the Eastern group had wide confidence intervals for the machine power measure (see also Figure A1 for outcome distributions and Figure A2 for spatial distributions of connected firms and TFP). In the following section, we assess these patterns using regression analysis.



(a) Revenue per worker

(b) TFP

(c) Machine power

(d) Working days

Figure 1: Outcomes by ethnic groups

Notes: The vertical red line represents mean values of each variable. TFP is calculated as a residual after regressing log revenue per worker on log number of workers and log machine power. Ethnic groups are defined according to the algorithm described in Section 3.2.

4 Cultural links and firm-level outcomes

Our baseline regression is an OLS model of the form:

$$Y_{idj} = \beta_0 + \beta_1 Connected_{idj} + \gamma_{dj} + \nu X_{idj} + \epsilon_{idj}, \tag{1}$$

where, Y_{idj} denotes an outcome for firm i, located in district d and operating in industry j. Outcomes include log revenue per worker, total factor productivity, and machine power. $Connected_{idj}$ is an indicator equal to one if the firm's owners are connected to a European country. In an alternative specification, we divide connected firms into three groups (German-owned, Jewish-owned, and Other Connected firms) and estimate a separate coefficient for each group. In both specifications, the omitted comparison group consists of firms owned by ethnic Russians or members of Eastern minority groups. All specifications include district-by-subindustry fixed

effects, γ_{dj}, so that connected and non-connected firms are compared within the same district and subindustry.[10]

In all specifications, we control for the logarithm of factory age, the number of employees, a dummy for urban location, and a dummy for a noble surname.[11] These are represented by vector X_{idj}. Controlling for factory age allows us to mitigate potential concerns that younger factories would be more likely to be connected and to invest in newer technology than incumbents due to technological path dependence for older factories. Controlling for the number of employees ensures that the sheer differences in scale of employment are not responsible for the "connected" firms' advantage; we do not have a prior on this coefficient. Controlling for urban location allows us to mitigate agglomeration effects, access to larger labor and product markets. Finally, controlling for surname nobility could partially mitigate differences in starting capital. The following subsections present the results for different outcome variables.

4.1 Productivity

Table 3 presents the main results for firms' productivity measures as dependent variables. Columns 1-3 report that "connected" firms had higher revenue per worker, higher total factor productivity, but not more machine power than non-connected firms. The economic effect of the owner's origins is substantial – "connected" firms had, on average, about 10% higher revenue per worker and about 9.2% higher total factor productivity. The effects are comparable to adding one more log point of labor or a third of the size of locating in a city (see Appendix Table B1 for coefficients on all control variables).

[10] We use industry and subindustry classifications as reported in the manufacturing census. On average, each of the 12 industries had about 40 sub-industries. For instance, 55% of the firms in the paper industry reported their subindustry as typography and 11% as paper production.

[11] Noble surnames are identified from the General Armorial of the Noble Families of the Russian Empire by 1917 (Noble, 1917).

Table 3: Connected firms and productivity

	log Revenue per worker	TFP	Machine Power	log Revenue per worker	TFP	Machine Power
	(1)	(2)	(3)	(4)	(5)	(6)
Connected	0.095***	0.088***	0.054			
	(0.022)	(0.023)	(0.044)			
German				0.113***	0.087***	0.018
				(0.032)	(0.033)	(0.142)
Jewish				0.097***	0.095***	0.046
				(0.025)	(0.025)	(0.047)
Other Connected				0.079***	0.067**	0.082
				(0.028)	(0.028)	(0.086)
Observations	10,739	10,739	9,531	10,739	10,739	9,531
Mean Dependent Variable	6.852	-0.014	25.776	6.852	-0.014	25.776
R-squared	0.670	0.629		0.670	0.629	
District × Sub-industry FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓

Notes: Robust standard errors clustered at district level. The outcome variable in columns 1 and 4 is log revenue per worker; columns 2 and 5 is residual TFP from a Cobb-Douglas production function of regressing log revenue on log total employment and log total machine power (+1). Columns 3 and 6 estimate Poisson pseudo-maximum-likelihood model, with the total machine power as the outcome, due to prevalence of zero values in the outcome variable. Note that the number of observations decreases in columns 3 and 6. This is because these firms have missing machine power. Controls are log factory age, a dummy for whether a factory is located in a city, log number of employees, and whether a last name is included in the Noble (1917).

In columns 4-6, we decompose connected firms into three subgroups – Germans, Jews, and Other Connected, leaving the non-connected subgroups (Russians and Eastern minorities) as a baseline. German- and Jewish-owned firms exhibited larger productivity in terms of both log revenue per worker and TFP. Again, we find that the coefficient on machine power is positive but not statistically significant. Thus, the productivity premium of "connected" firms may have stemmed from more efficient factor allocation or management practices rather than higher capital investments. Overall, the results provide strong statistical evidence on the importance of an owner's cultural background for a firm's productivity.[12]

4.2 Machinery type

Next, we explore the proximate sources of the productivity advantage of connected firms, testing if they were more likely to possess advanced machinery. According to the manufacturing census,

[12]We further test the robustness of these estimates to several specification and sample choices: 1) only looking at firms with more than 15 employees (Table B2), and 2) dropping Jewish-owned firms (Table C4).

41% of the firms did not have machines and employed only manual labor. Another 13% used animal power, usually horses, in addition to human labor. The rest of the sample had at least one mechanical device: steam engine (33%), water or wind wheel (14%), or a more advanced type of machinery such as locomotive, gas, kerosene, or benzine engine (11%).

Based on these data, we generate three dependent dummy variables: 1) Has at least one machine; 2) Has at least steam engine; 3) Has above median machine power per engine, conditional on possessing a steam engine. The first takes the value 1 if a firm has any mechanical device (46% of the sample). The second takes the value 1 if a firm has a steam engine, locomobile, or other type of advanced machinery (44%). The difference between the two is that the second does not include firms with water or wind wheels as power sources.

The third takes the value 1 if a firm's machine has a horsepower above the median level. This variable captures the variation in intensive margin, which was substantial: the average horsepower per machine ranged from 1 to 873.

Table 4: Connected firms and machine types

	Has at least one machine (1)	Has at least steam (2)	Above-median power per machine (3)	Has at least one machine (4)	Has at least steam (5)	Above-median power per machine (6)
Connected	0.013	0.017**	0.031			
	(0.008)	(0.008)	(0.023)			
German				0.041***	0.039***	0.043*
				(0.014)	(0.013)	(0.025)
Jewish				0.008	0.010	0.013
				(0.008)	(0.008)	(0.025)
Other Connected				0.019*	0.026**	0.058**
				(0.011)	(0.010)	(0.025)
Observations	12,934	12,934	5,173	12,934	12,934	5,173
Mean Dependent Variable	0.460	0.431	0.626	0.460	0.431	0.626
District × Sub-industry FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓

Notes: The outcome variable of columns 1 and 4 is whether a firm owned any engine type. Columns 2 and 5 are limited to only those that used at least steam (but may not have steam, but more advanced engine types, such as gas, petrol, electricity). In columns 3 and 6 the outcome is having above median machine power, conditional on possessing a steam engine. Controls are as in Table 3.

Table 4 presents the estimation results. It shows that the advantage of "connected" firms was largely driven by entrepreneurs of German origin. German and Other Connected firms were more likely to have machine power, to use steam power, and to have more modern machines, as captured by higher power per machine. The results for Jewish firms are intriguing: their productivity advantage stemmed not from capital investments but rather from non-tangible assets or management practices, which we explore in the next subsection. In general, Table 4 shows that "connected" firms were not homogeneous: the advantage of German-owned firms stemmed from higher and better machinery, while Jewish firms did not possess machinery ad-

vantage. Other Connected firms were somewhere in between since they had significantly more machinery, but the coefficients are generally lower than for the German firms.

4.3 Management practices

Differences in productivity could also stem from variations in management practices, i.e. decisions not directly related to the amount of capital and labor employed. The census provides two measures that can be attributed to management practices. The first is the number of days per year that a factory operates. Firms that stayed open more days per year left capital idle for less time and generally resembled industrial factory-like operations more than seasonal manufacturing firms did. They also succeeded in retaining labor through agricultural high seasons.[13] The second is partnership, namely if a firm has more than one owner with different surnames. Forming a partnership could introduce diverse expertise, thus creating more opportunities for innovation.[14]

Table 5: Connected firms and management practices

	log Working Days in 1894	Partnership	log Working Days in 1894	Partnership
	(1)	(2)	(3)	(4)
Connected	0.018*	0.040***		
	(0.010)	(0.005)		
German			0.012	0.044***
			(0.013)	(0.010)
Jewish			0.025**	0.030***
			(0.011)	(0.005)
Other Connected			0.001	0.068***
			(0.013)	(0.009)
N	12,696	12,956	12,696	12,956
Mean	5.246	0.042	5.246	0.042
R-squared	0.649	0.262	0.650	0.266
District × Sub-industry FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓

Notes: Robust standard errors clustered at district level. The outcome variable in columns 1 and 3 is the log number of days the firm was open; in columns 2 and 4 is dummy for a partnership. Controls as in Table 3.

[13] See Gregg and Matiashvili (2022) for a discussion of the relationship between working days and factory-like operations in the late Russian Empire.

[14] See Lamoreaux (1995), Lamoreaux and Rosenthal (2005), Artunç and Guinnane (2019), and Gregg (2020), among many others, on the effect of ownership type on firm performance.

Table 5 presents the results. "Connected" firms operated more days per year (column 1) and were more likely to operate as a partnership (column 2). Next, we again look at the decomposition of the connected group into different subgroups. As discussed in baseline results, we found that Jewish-owned firms had higher TFP and revenue per worker than Russian and Eastern groups, but did not seem to have more capital. Here, we see a partial answer to the riddle. Jewish-owned firms were more likely to work more days during the year (column 3), which would have generated higher revenue per worker. They were also more likely to form a partnership (column 4), which would have offered more diversified expertise in management. German-owned firms exhibited similar patterns of ownership. Finally, while the Other Connected firms did not operate longer, they were also more likely to form partnerships.

4.4 Contribution of technology and management to the productivity gap

So far, we have shown that the firms we classify as "connected" were more productive, more likely to use advanced machinery and implement better management practices. A natural question to ask is how much the differences in machinery and management practices explain the productivity gaps.

To assess how much of the productivity premium is accounted for by observed technology and operating characteristics, we use the decomposition proposed by Gelbach (2016). The baseline regression uses results from Table 3: regressing log revenue per worker on "connected" status, log firm age, log employment, city location, noble status, and district-by-subindustry fixed effects. Additionally, we include all the observables we found to be significantly different between "connected" and "non-connected" firms: indicators for steam or more advanced power sources and above-median horsepower,[15] log working days, and partnership status. Using a common estimation sample, we decompose the change in the connected coefficient into additive contributions from these characteristics. Each contribution equals the characteristic's coefficient in the full productivity regression multiplied by the "connected" coefficient in a separate regression of that characteristic on "connected" status, baseline controls, and the fixed effects. We group the two machinery measures into a technology contribution. We use 1,000 bootstrap replications, resampling all districts.

Table 6 reports the Gelbach decomposition of the productivity premium. Observed technol-

[15] Unlike in Table 4, in this decomposition, this variable is zero if a firm has no machine power, to avoid dropping a large part of the sample and potentially bias our results.

Table 6: Decomposition of the connected productivity premium

	Coefficient / contribution	Share (%)	p-value
Panel A: Log revenue per worker			
Baseline connected premium	0.0926	—	< 0.001
Remaining connected premium	0.0686	—	< 0.001
Technology (steam and horsepower)	0.0060	6.5	0.080
Working days	0.0126	13.6	0.069
Partnership status	0.0054	5.9	< 0.001
Total accounted for	**0.0240**	**25.9**	0.002
Observations	10,577		
District clusters	567		
Panel B: TFP			
Baseline connected premium	0.0866	—	< 0.001
Remaining connected premium	0.0724	—	< 0.001
Technology (steam and horsepower)	-0.0034	-3.9	0.038
Working days	0.0125	14.5	0.069
Partnership status	0.0050	5.8	0.003
Total accounted for	**0.0142**	**16.4**	0.058
Observations	10,577		
District clusters	567		

Notes: Contributions are calculated using the Gelbach decomposition. Each panel uses a fixed estimation sample selected from its full specification; the samples may differ across panels. All models include log firm age, log employment, city location, noble status, and district-by-subindustry fixed effects. The full model jointly includes steam or more advanced power sources, above-median horsepower, log working days, and partnership status. Technology combines the two machinery measures. Inference uses 1000 requested bootstrap replications resampling entire districts. Shares are descriptive point estimates relative to the baseline connected premium; p-values are two-sided normal-based bootstrap Wald tests of the corresponding coefficients or contributions, not tests of the percentage shares. Panel A coefficients are in log points; Panel B coefficients use the units of the TFP variable. The decomposition does not identify causal mediation effects.

ogy and operating characteristics jointly account for 0.024 log points in revenue per worker, or 25.9% of the baseline premium ($p = 0.002$). Technology accounts for 6.5%, working days for 13.6%, and partnership status for 5.9%. The technology and working-days contributions are statistically significant at the 10% level, while the partnership contribution is significant at the 1% level. For TFP, the same characteristics jointly account for 16.4% of the baseline premium ($p = 0.058$). Working days and partnership status contribute positively, whereas technology makes a small negative contribution (-3.9%; $p = 0.038$), indicating that accounting for the machinery alone would widen the conditional TFP premium, holding the other added characteristics in the model fixed. The remaining connected premium is positive and statistically significant for both outcomes. Importantly, observed capital and management practices account for about one quarter of the observed productivity gap, suggesting that other unobserved characteristics

of these firms played a dominant role.

5 Testing the knowledge transmission mechanism

Having established baseline differences in productivity, capital, and management practices between connected and non-connected firms, we next explore the mechanisms behind this variation. We conjecture that "connected" firms enjoyed lower transaction costs in the adoption of Western technical and organizational know-how. However, testing this hypothesis is challenging, since the manufacturing census does not contain data on firms' foreign trade operations or any information on contacts with foreign companies. Hence, we employ additional data sources and estimation techniques to test the knowledge transmission mechanism. The following four subsections describe these empirical exercises.

5.1 1893 Chicago World's Fair

The Chicago World Fair (also known as the World's Columbian Exposition) was held in Chicago in 1893, representing the technological and cultural advancements of industrial nations in the late 19th century. The Russian Empire had 1,022 exhibits. While most of them were inventions or individual art pieces, approximately a fifth were private firm exhibits demonstrating the firms' products. The Russian Ministry of Finance published a catalog of these exhibits with blurbs describing each firm in detail: industry, founding year, output, revenue, and trade, among others (Ministry of Finance, 1893). We were able to match 122 firms from the exhibition catalog to the manufacturing census. This sub-sample is biased toward more productive and innovative firms since they were selected by the government to demonstrate the industrial progress of the Empire.[16]

The advantage of these data is that we observe whether firms: (1) exported their products abroad to any foreign country, (2) exported their products to a European country, (3) imported materials from any foreign country, and (4) imported materials from a European country. In addition, the fair firms show sufficient variation in the cultural origins of their owners, as assigned by our algorithm: 37% Russian, 38% Jewish, 10% German, and 10% Other Connected. Hence, we can perform a regression analysis with import and export variables on the left-hand side,

[16]Table D6 shows that these firms had 25% higher revenue per worker, and 30% more machine power than their counterparts.

keeping in mind that the sample is biased toward more productive firms.

Table 7: Foreign Trade: Data from 1893 Chicago World Fair

	Full sample				Matched sample			
	Abroad		To Europe		Abroad		To Europe	
	Import (1)	Export (2)	Import (3)	Export (4)	Import (5)	Export (6)	Import (7)	Export (8)
German	0.062	0.180	0.106*	0.315**	-0.125	0.141	-0.042	0.338**
	(0.051)	(0.161)	(0.044)	(0.119)	(0.095)	(0.125)	(0.099)	(0.120)
Jewish	0.019	0.007	0.016	0.039	0.011	0.011	0.076	0.068
	(0.059)	(0.101)	(0.087)	(0.033)	(0.051)	(0.133)	(0.062)	(0.035)
Other Connected	0.148***	0.161	0.126***	0.153	0.247*	0.207	0.202	0.210*
	(0.037)	(0.205)	(0.018)	(0.133)	(0.104)	(0.275)	(0.101)	(0.092)
N	227	249	191	207	107	114	89	92
Mean	0.357	0.305	0.162	0.135	0.383	0.360	0.180	0.152
R-squared	0.251	0.139	0.120	0.167	0.249	0.120	0.127	0.245
Industry and sub-industry FE	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓

Notes: Robust standard errors clustered at the industry level in parentheses. Panel A includes all firms that participated in the 1893 Columbian Fair. Panel B includes firms we were able to match to the 1894 Manufacturing Census. Import abroad (column 1) is defined as an indicator of whether a firm reports imports from abroad. Exports abroad (column 2) is defined as an indicator for whether a firm reports sales abroad. European import (column 3) is limited to import from Western Europe only. The same logic applies to exports in column 4.

Table 7 presents these results. Columns (1)-(4) show the results for a full sample of firms at the fair. Columns (1) and (2) present suggestive evidence that Other Connected firms were more likely to trade abroad. However, we are particularly interested in trade with Europe, shown in columns (3) and (4). We see that German and Other Connected firms were more likely to engage in trade with Europe. Similar patterns hold for the sample of firms matched to the 1894 census in columns (5)-(8), although the statistical significance of these estimates is lower because of a smaller sample.

The results suggest that even among the most successful firms in the Russian Empire, the differences in trade behavior reflected owners' cultural origins. Connected owners were significantly more likely to trade with Europe and benefit not only directly in the form of higher revenue but also indirectly in the form of know-how transfer from more advanced economies. Although we are unable to observe technology transfer directly, we can state that it was likely, given the economic ties we observe in the trade data.

5.2 Comparative advantage of German entrepreneurs in the Russian Empire

If the connected firms' productivity premium originates from the transfer of know-how, then the premium should be most pronounced in industries where the origin country had a comparative

advantage at the time. In this subsection, we test whether firms owned by German-origin entrepreneurs in Russia had a productivity advantage in the same industries as Germany did in the late 19th century. To test this, we estimate the same Equation (1) separately for each industry.

A large body of literature in German economic history documents that, after the unification in 1871, German economy experienced an industrial boom "especially in machinery, chemicals, and electro-technical goods" (Hungerland and Wolf, 2022). Germany's increasing industrial might in heavy machinery and chemicals came to rival Britain as Europe's primary industrial nation in the decades preceding World War I (Mokyr, 1990). By 1900 the German chemical industry dominated the world market for synthetic dyes with three major firms (BASF, Bayer, and Hoechst) producing about 60% of the world supply of dyestuffs and selling about 80% percent of their production abroad (Kindleberger, 1975).[17]

Based on these accounts and given the industry classification in the 1894 manufacturing census, we expect that firms owned by entrepreneurs of German origin exhibited higher productivity in industries such as Chemicals, Metals, and Machines, and possibly other industries that employed heavy machinery to process raw materials into final products. Figure 2 shows the estimated coefficients on the German dummy for each industry in our sample. Indeed, we find a large and statistically significant productivity premium in chemicals: German-owned firms in this industry had, on average, 100% higher revenue per worker[18] than Russian-and Eastern Minority-owned firms.

[17] See also Malein (2021) on the impact of the German minority on the industrialization across Russian regions, and Natkhov and Vasilenok (2021) on the diffusion of agricultural technologies from German settlers to Russian peasants in the Middle Volga region.

[18] Transforming 0.694 log points to percent.

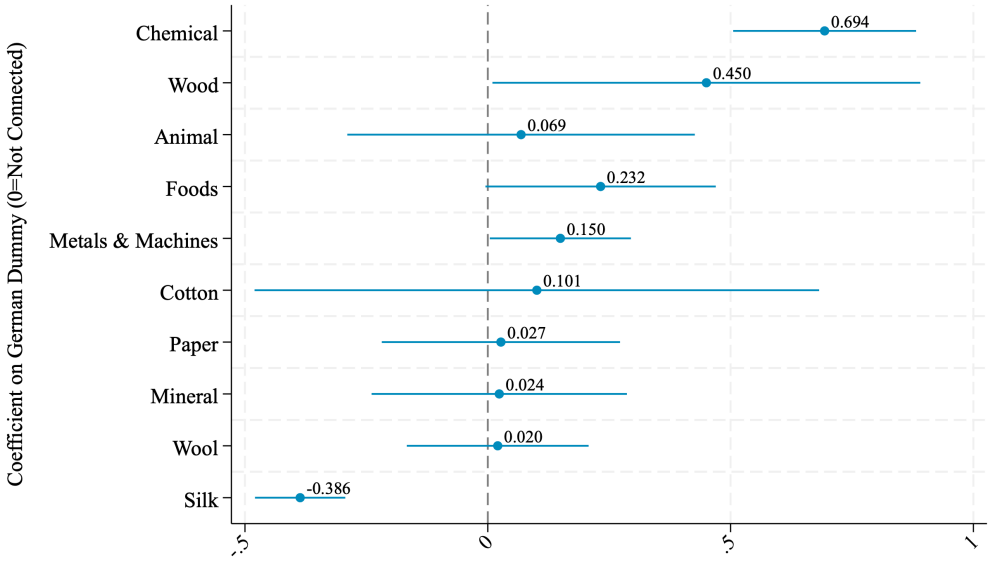


Figure 2: German productivity premium by industry (log Revenue per Worker)

Notes: The outcome variable in all specifications is log revenue per worker. The coefficients on the German dummy show the average difference in log revenue per worker between German-owned firms and non-connected firms conditional on firm age, number of employees, urban location, and district by subindustry fixed effects. Bars represent the 95% confidence interval. Firms classified by industry as in the 1894 manufacturing census.

Consistent with the proposed mechanism, we also observe a positive and statistically significant coefficient for Metals and Machines. Similarly, the positive coefficients for Wood and Food processing imply that German firms in these industries probably benefited from imported machinery, allowing them to process raw materials more efficiently. Interestingly, for the textile industry (Cotton and Wool), the estimated coefficient is zero, and for Silk production, it is even negative. Hence, we do not observe any "German premium" for industries in which Germany had no comparative advantage at the time.[19]

5.3 Local spillover effects

In the previous subsections, we presented indirect evidence of technology diffusion from abroad. However, a significant share of innovation spillovers take place locally when less productive firms try to emulate a domestic "role model" in their industry. We then pose a question, did non-connected firms with higher exposure to "connected" firms operating in the same market

[19] In Appendix E.1, we look at all connected groups *except for* Germans. The coefficient on the chemical industry drops to zero, suggesting that the difference between connected and non-connected firms stemmed exclusively from the German comparative advantage. Appendix E.2 presents qualitative evidence on German-born entrepreneurs in the Russian chemical industry, showing that they had direct connections to Germany enabling the transmission of knowledge.

adopt innovations at a higher rate than those with lower exposure? To answer this question, we calculate for each non-connected firm a continuous measure of "exposure to connected firms" as the share of labor employed by connected firms in a given district and industry, or more formally:

$$Exposure_{idj} = \frac{\text{Number of employees of connected firms }_{idj}}{\text{Total number of employees of all firms}_{idj}} \tag{2}$$

We then include this variable in the regression equation to compare the productivity measures of a non-connected firm in a given district-industry to other non-connected firms in a different district but the same province and industry. Hence, we estimate the following equation:

$$Y_{idj} = \alpha_0 + \alpha_1 \times Exposure_{idj} + \delta X_{idj} + \psi_{pj} + \varepsilon_{idj}. \tag{3}$$

where Y_{idj} is an outcome for non-connected firm (i), located in district (d) and operating in industry (j); $Exposure_{dj}$ is the share of workers in the firm's district-industry cell who are employed by connected firms; X_{idj} is a vector of firm-level controls; and ψ_{pj} denotes province-by-industry fixed effects. The coefficient α_1 therefore captures the relationship between local exposure to connected firms and the outcomes of non-connected firms, conditional on comparisons within the same province and industry.

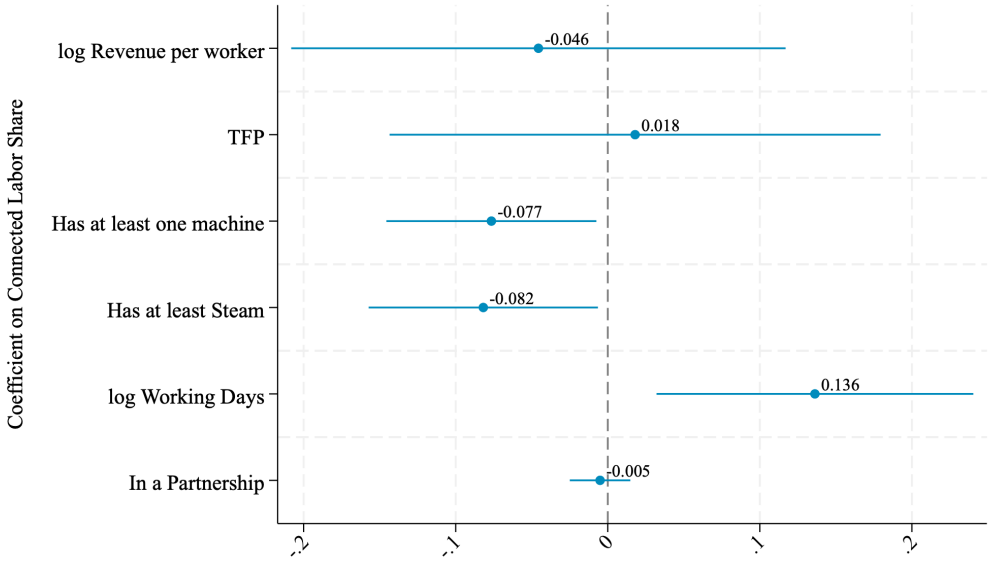


Figure 3: Spillovers from connected to non-connected firms

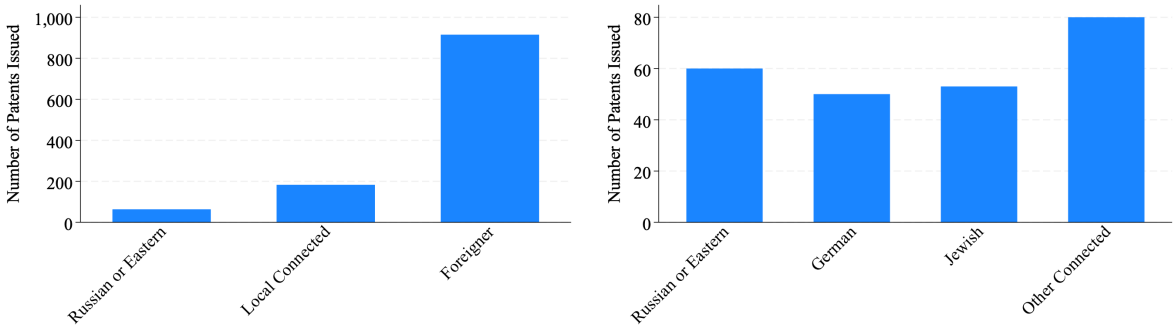
Notes: The coefficients on the share of connected firms show the average differences in productivity measures between non-connected firms with different exposure to connected firms conditional on firm age, number of employees, urban location, and province-by-industry fixed effect fixed effects. Bars represent 95% confidence interval.

Figure 3 presents the estimated coefficients on $Exposure$ for non-connected firms across production and organizational outcomes. We find no statistically significant association between exposure to connected firms and either revenue per worker or TFP. Greater exposure is associated with more working days per year, an important indicator of factory-like operation (Gregg and Matiashvili, 2022), but with a lower likelihood of having at least one machine or using steam or more advanced power sources. Partnership status shows no statistically significant association with exposure. These cross-sectional patterns provide limited evidence of local emulation of management practices.

5.4 Patents

Patents are often used as a proxy for innovative activity. We digitized the universe of patents issued in the Russian Empire in 1892-1896, around the time the manufacturing census was conducted. There were a total of 1,161 patents issued to individuals over this period.[20] Most of them, 915, were issued to foreign nationals (see Figure 4a), part of it due to cross-patenting from other nations. However, even within the citizens of the Russian Empire, there remain stark differences in patenting by ethnicity. Of the remaining 246 patents, 50 had been assigned to Germans, 53 to Jews, 80 to other Western-sounding last names, 58 to Russians and only 2 to Eastern-sounding last names (see Figure 4b; 3 were unassigned). The fact that Russians patented at similar levels as Germans is particularly striking, given that Russians accounted for 44.3% of the Empire's population, and Germans for only 1.43%.

[20] We drop patents issued to corporations.



(a) Number of patents assigned to foreigners and locals

(b) Number of patents assigned to locals, by ethnicity

Figure 4: Patents by citizenship and ethnicity, 1892-1896

Notes: The data come from the directory of all patents issued by the Russian Empire in the period 1892-1896 (Department of Trade and Manufacturing, 1897). (a) Foreigners are identified when referred to as "foreigner" or "foreign subject" or "subject of country X". Local Connected group is defined as having German, Jewish, or Other Connected last names. This classification, due to a small sample size, was conducted by the authors, and differences reconciled.

5.5 Location

Were connected firms more likely to enjoy the benefits of cities compared to the non-connected firms? It is well-documented that locational choices have a big effect on outcomes. To make sure we were not picking up this urban versus rural choice of factories, we have included dummies for urban location throughout. However, a deeper dimension to this choice in our case may be that the connected entrepreneurs benefit *more* from locating in major cities, as big cities provide access to larger markets and easier connection to international trade. While we cannot directly test the latter part of the argument, we can see whether connected entrepreneurs benefited more from locating in cities, providing at least suggestive evidence.

Table 8: Connected Entrepreneurs and Location Choices

	log Revenue per worker	TFP	Machine Power	log Revenue per worker	TFP	Machine Power
	(1)	(2)	(3)	(4)	(5)	(6)
Connected × City >100k pop.	0.083*	0.067	0.269*			
	(0.043)	(0.047)	(0.141)			
German × City >100k pop.				0.144**	0.122*	-0.010
				(0.066)	(0.071)	(0.277)
Jewish × City >100k pop.				0.057	0.049	0.245*
				(0.052)	(0.058)	(0.136)
Other Connected × City >100k pop.				0.107**	0.087*	0.497*
				(0.047)	(0.051)	(0.301)
City >100k pop.	0.154*	0.173**	-0.157	-0.082	0.167**	-0.134
	(0.088)	(0.082)	(0.118)	(0.101)	(0.082)	(0.123)
Connected	0.078***	0.075***	0.001			
	(0.027)	(0.027)	(0.046)			
German				0.074*	0.047	0.080
				(0.042)	(0.043)	(0.071)
Jewish				0.084***	0.086***	0.007
				(0.028)	(0.029)	(0.052)
Other Connected				0.058*	0.049	-0.031
				(0.034)	(0.033)	(0.053)
N	10,739	10,739	9,531	10,739	10,739	9,531
Mean	6.852	-0.014	25.776	6.852	-0.014	25.776
R-squared	0.667	0.626		0.670	0.626	
District × Sub-industry FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓

Notes: Robust standard errors clustered at District level. "City > 100k pop" is a binary variable for cities with more than 100,000 population in the 1897 Population Census. Please refer to Table 3 notes for details on outcome variables.

We identify seventeen largest cities from the 1897 Russian Empire Population Census with a population greater than one hundred thousand. First, we find that Connected entrepreneurs were more likely to locate in a big city (21.7% vs 14.8%). We then repeat the analysis from Table 3 but include the interaction terms with the binary variable of whether a factory was located in one of these major cities. Indeed, we find that the interaction term on "connected" and locating in a major city is positive for all outcomes, and marginally significant for two (Columns 1 - 3 of Table 8). In terms of log revenue per worker, the interaction was positive for all ethnicities,

and statistically significant for the German and Other Connected groups (Columns 4-6 of Table 8). For TFP, same patterns hold but are only marginally significant. For machine power, we find marginally significant positive interactions for the Jewish and Other Connected groups. These results suggest that cities were more beneficial to the connected than the non-connected group, potentially due to higher access to communication with and transport to Europe.[21]

6 Testing for alternative mechanisms

In this section, we test for other potential mechanisms, such as initial wealth, education, ethnic bias in demand for a firm's products, or ethnic network effects in the supply of inputs. We find that these possible explanations for productivity premium are less likely than the knowledge transmission mechanism.

6.1 Starting capital

The most salient competing mechanism is entrepreneurs' initial wealth that might correlate with cultural origins, enabling "connected" owners to invest in more and newer machinery from the beginning. While we do not have data on a firm's starting capital, we can exploit a large variation in capital per worker in our data to isolate the initial capital mechanism. In doing so, we compare log revenue per worker and TFP of firms that used no machines. In this specification, the two are essentially equivalent, given that capital does not contribute to the TFP calculation. If the productivity premium of the "connected" firms came mainly from larger starting capital, we should see no difference in productivity among firms without machines, controlling for the number of workers, and operating in the same industry and district. If, on the other hand, the productivity advantage persists even among firms without capital, we can at least tenuously conclude that something beyond initial wealth is responsible for the advantage. Hence, we estimate Equation (1) on the sub-sample of firms without machines.

Table 9 presents the results. The coefficient on log revenue per worker and TFP are roughly of the same magnitude as those in Table 3. The pattern of the coefficients is also similar to the whole sample estimation for the German and Jewish firms. It is also notable that there are no differences in the average number of employees between the connected and non-connected

[21] In Appendix G, we show that the connected entrepreneurs did not benefit from shorter physical distances to the European borders, suggesting that the cultural connections and communication technologies likely played a more important role.

Table 9: Sub-sample of firms without machines

	log Revenue per worker (1)	TFP (2)	log Revenue per worker (3)	TFP (4)
Connected	0.098***	0.098***		
	(0.033)	(0.033)		
German			0.137**	0.137**
			(0.062)	(0.062)
Jewish			0.100***	0.100***
			(0.034)	(0.034)
Other Connected			0.074*	0.074*
			(0.043)	(0.043)
N	3,988	3,988	3,988	3,988
Mean	6.525	-0.027	6.525	-0.027
R-squared	0.712	0.714	0.712	0.714
District × Sub-industry FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓

Notes: Robust standard errors clustered at the District level. The sample is limited to the firms without any machines. Refer to Table 3 for details on outcome variables and controls.

firms with no machines, suggesting that these firms were similar along the margin that may reflect differences in starting finances. We cannot rule out unobservable advantages such as savings and access to higher-quality inputs.[22]

6.2 In-group bias

A potential confounder of our results is the fact that a lot of connected entrepreneurs lived in majority-connected districts. For instance, districts with a larger share of the Jewish population within the Pale of Settlement also had a higher share of Jewish-owned firms. These firms might have performed better because locals were more willing to purchase goods from their compatriots rather than from out-group entrepreneurs. We address this concern in Table 10, where we replicate Table 3 on a restricted sample of districts with more than 50% of ethnic Russians according to the 1897 population census. In these districts, non-Russian entrepreneurs would have had a smaller in-group advantage than Russian entrepreneurs, which would introduce a downward bias in our estimates on connected firms dummy. Instead, the results are almost identical to Table 3, suggesting that they are likely not driven by in-group bias in non-Russian districts.

[22] In Appendix F, we show that the "connected" premium could also not be explained by the higher human capital in the locations of these firms.

Table 10: Connected firms' productivity in districts with more than 50% Russian population

	log Revenue per worker	TFP	Machine Power	log Revenue per worker	TFP	Machine Power
	(1)	(2)	(3)	(4)	(5)	(6)
Connected	0.091***	0.084***	0.051			
	(0.025)	(0.023)	(0.045)			
German				0.107**	0.072*	-0.010
				(0.043)	(0.040)	(0.176)
Jewish				0.090***	0.088***	0.042
				(0.028)	(0.026)	(0.049)
Other Connected				0.090***	0.080***	0.091
				(0.032)	(0.029)	(0.098)
Observations	9,478	9,478	8,065	9,478	9,478	8,065
Mean Dependent Variable	6.817	-0.035	27.477	6.817	-0.035	27.477
R-squared	0.669	0.626		0.669	0.626	
District × Sub-industry FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓

Notes: Robust standard errors clustered at the District level. The sample is limited to the districts with majority Russian population. Refer to Table 3 for details on outcome variables.

6.3 Network effects

Similar to the in-group bias, but a somewhat distinct possible confounder to the knowledge diffusion mechanism is the ethnic networks mechanism – firms with same-ethnicity owners may be able to access cheaper input and larger output markets through ethnic networks, both locally and through diasporas in other provinces.[23] The network effect could also enhance knowledge diffusion – individuals of the same ethnicity may transmit entrepreneurial know-how within ethnic networks. Both of these mechanisms suggest a positive correlation between a firm's productivity and a share of firms with same-ethnicity owners in the same industry (but not the same primary activity - that is, direct competition) and district. Our data, however, do not allow us to reconstruct networks of firms and entrepreneurs. Instead, we repeat the analysis presented in equation (1) with an additional interaction variable reflecting the number of firms in the same district and the overall industry owned by the same ethnicity-names as the i firm. This way, we proxy for upstream-downstream firms owned by the same-ethnicity entrepreneurs in a given

[23] Spitzer (2021) shows that Jewish emigration from the Russian Empire to the United States in same period exhibited a strong spatial diffusion pattern within social networks of relatives and friends.

market.

Table 11: Benefits of nearby upstream or downstream factories owned by same ethnicity

	Log Revenue per Worker		TFP	
	(1)	(2)	(3)	(4)
Share same ethnicity	0.054	0.176*	0.106	0.226**
	(0.114)	(0.102)	(0.105)	(0.102)
Jewish	0.309***	0.164**	0.268***	0.180**
	(0.075)	(0.082)	(0.069)	(0.082)
German	0.229***	0.216***	0.164**	0.185***
	(0.082)	(0.066)	(0.071)	(0.064)
Other Connected	0.217***	0.140**	0.193***	0.160**
	(0.073)	(0.066)	(0.066)	(0.066)
Share same ethnicity × Jewish	-0.492***	-0.134	-0.400***	-0.165
	(0.155)	(0.185)	(0.142)	(0.184)
Share same ethnicity × German	-0.280	-0.239	-0.201	-0.194
	(0.204)	(0.154)	(0.190)	(0.152)
Share same ethnicity × Other Connected	-0.387**	-0.097	-0.386***	-0.174
	(0.163)	(0.173)	(0.148)	(0.171)
Observations	13 592	10 739	13 592	10 739
Mean	6.660	6.631	-0.149	-0.173
R-squared	0.215	0.670	0.217	0.629
District FE	✓		✓	
District × Sub-industry FE		✓		✓
Firm Controls	✓	✓	✓	✓

Notes: Robust standard errors clustered at the District level. Nearby factories are defined as operating in the same district and industry. Refer to Table 3 for details on outcome variables.

Table 11 presents the results. Columns 1 and 3 present baseline results with district fixed effects only, while Columns 2 and 4 add district by subindustry fixed effects. The results suggest that having more firms in a district owned by the same ethnicity as one's own does not improve a firm's outcomes. If anything, it seems to be detrimental to productivity. All coefficients for

the interaction terms are negative and often significant. These results suggest that the cheaper inputs or local networks story does not hold in this setting. More likely, having a higher share of upstream/downstream firms owned by the same ethnicity also translates to a higher share of direct competitors of the same ethnicity. If owners prefer to trade with same-ethnicity owners, this would create even higher competition within the ethnic enclaves, leading to negative interaction terms.

7 Conclusion

We document substantial productivity advantages of industrial firms with cultural connections to the technological frontier in the late 19th century Russian Empire. We show that these productivity advantages came from both the adoption of advanced machinery and superior management practices. We use additional data sources to show that more patents were awarded to "connected" ethnic groups, and "connected" firms were more likely to trade with Europe. "Connected" firms also exhibited higher productivity in the same industries as their European counterparts, i.e., the chemical industry for German-owned firms.

Our results provide new insights into the development paths of late-industrializing economies. Consider, for example, the contrasting experiences of the Russian and Ottoman Empires in the late 19th-early 20th century. Both had rigid economic institutions and were governed by autocratic political regimes. The Russian Empire, however, demonstrated impressive industrial growth of about 4% per year for almost three decades before World War I (Markevich and Nafziger, 2017), while in the Ottoman Empire industrialization remained very limited (Pamuk, 2019). Both empires were multi-ethnic, but only in the Russian case several minorities had direct cultural connections with Western Europe. We posit that the presence of "connected" minorities in Russia compensated, to some extent, for institutional deficiencies and allowed for relatively faster growth of the private manufacturing sector. The Ottomans were deprived of that advantage, and industrialization before 1914 was mostly confined to the government-assisted construction of railways, while the private sector remained largely agrarian.

Unpacking the "black box" of cultural connections is the next step in studying technology diffusion. How do technologies and management practices spread through individual and family ties? What explains the variation in the extent of technology adoption among connected groups? How did best practices spread from high- to low-performing groups? These questions are worth

exploring to advance our understanding of the sources of productivity variation across firms and countries.

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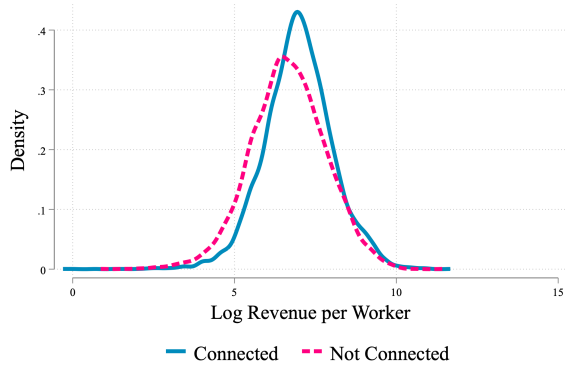
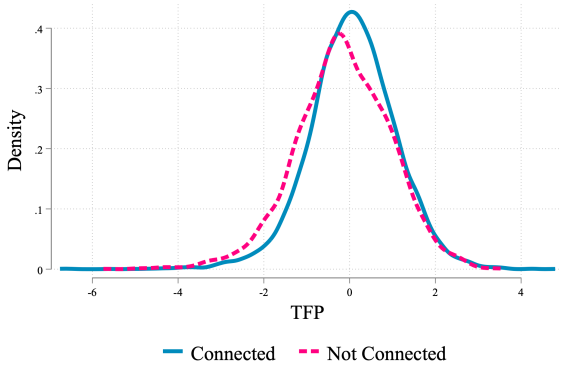
On-line Appendix

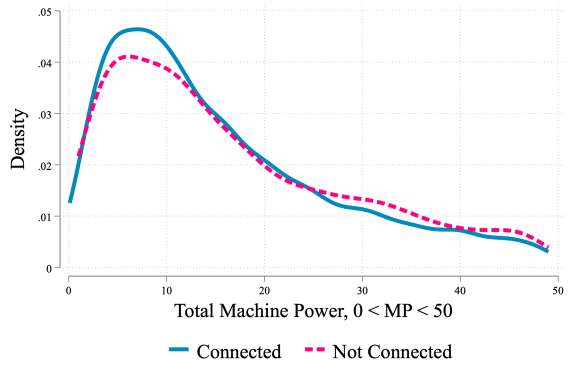
A Descriptive Statistics



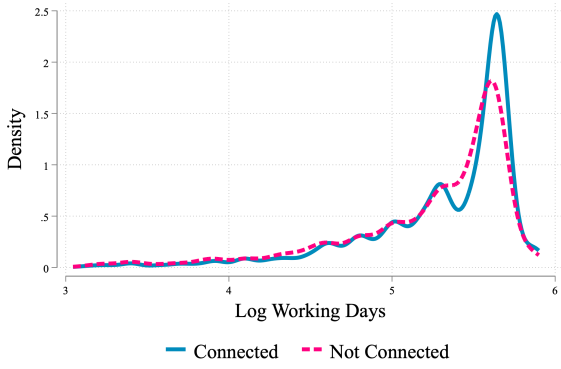
(a) Log Revenue Per Worker



(b) TFP



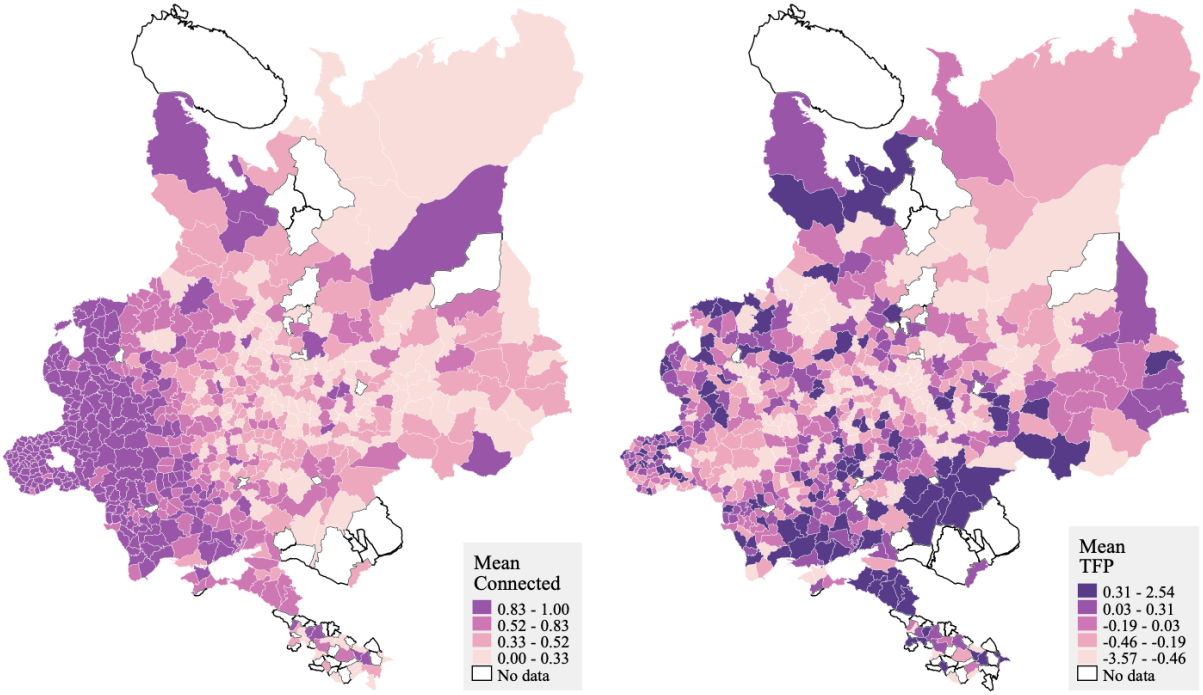
(c) Log Machine Power Per Worker



(d) Log Working Days

Figure A1: Density of select outcomes by group

Notes: Kernel densities use Epanechnikov kernel. TFP is calculated as a residual after regressing log Revenue per worker on log Number of workers and log Machine power (+1). Ethnic groups are defined as probable ethnic identity of the firm's owner according to the algorithm described in Section 3.2.



(a) Share Connected firms (b) Mean TFP

Figure A2: Spatial Distribution of Connected Firms and TFP

Notes: The shapefile is from Kessler and Markevich (2021). TFP is calculated as a residual after regressing log Revenue per worker on log Number of workers and log Machine power (+1). Ethnic groups are defined as probable ethnic identity of the firm's owner according to the algorithm described in Section 3.2.

B Results, continued

B.1 Showing controls

Table B1: Connected firms and productivity (with control variables shown)

	log Revenue per worker	TFP	Machine Power	log Revenue per worker	TFP	Machine Power
	(1)	(2)	(3)	(4)	(5)	(6)
Connected	0.095***	0.088***	0.054			
	(0.022)	(0.023)	(0.044)			
German				0.113***	0.087***	0.018
				(0.032)	(0.033)	(0.142)
Jewish				0.097***	0.095***	0.046
				(0.025)	(0.025)	(0.047)
Other Connected				0.079***	0.067**	0.082
				(0.028)	(0.028)	(0.086)
log Age	0.043***	0.043***	0.001	0.043***	0.043***	0.001
	(0.007)	(0.007)	(0.014)	(0.007)	(0.007)	(0.014)
log Num. Empl.	0.075***	0.054**	0.925***	0.075***	0.054**	0.925***
	(0.022)	(0.024)	(0.045)	(0.022)	(0.024)	(0.046)
Factory is located in a city	0.275***	0.260***	0.061	0.275***	0.259***	0.061
	(0.048)	(0.045)	(0.054)	(0.048)	(0.044)	(0.054)
Noble last name	-0.033	-0.029	0.006	-0.034	-0.033	0.009
	(0.026)	(0.025)	(0.058)	(0.026)	(0.026)	(0.054)
Observations	10,739	10,739	9,531	10,739	10,739	9,531
Mean Dependent Variable	6.852	-0.014	25.776	6.852	-0.014	25.776
R-squared	0.670	0.629		0.670	0.629	
District × Sub-industry FE	✓	✓	✓	✓	✓	✓

Notes: See notes to Table 3.

B.2 Larger firms

The inclusion criterion for this census was rather loose: a factory was included in the manufacturing census if one of the following were true: it had 15 employees, a steam boiler, a steam engine, or other factory devices. It is therefore possible that, by including many smaller factories possibly more likely to be operated by locals, we bias our results upwards. Here, we repeat the main productivity results, limiting our sample to factories with 15 or more employees.

Table B2: Productivity of larger connected firms
(more than 15 employees)

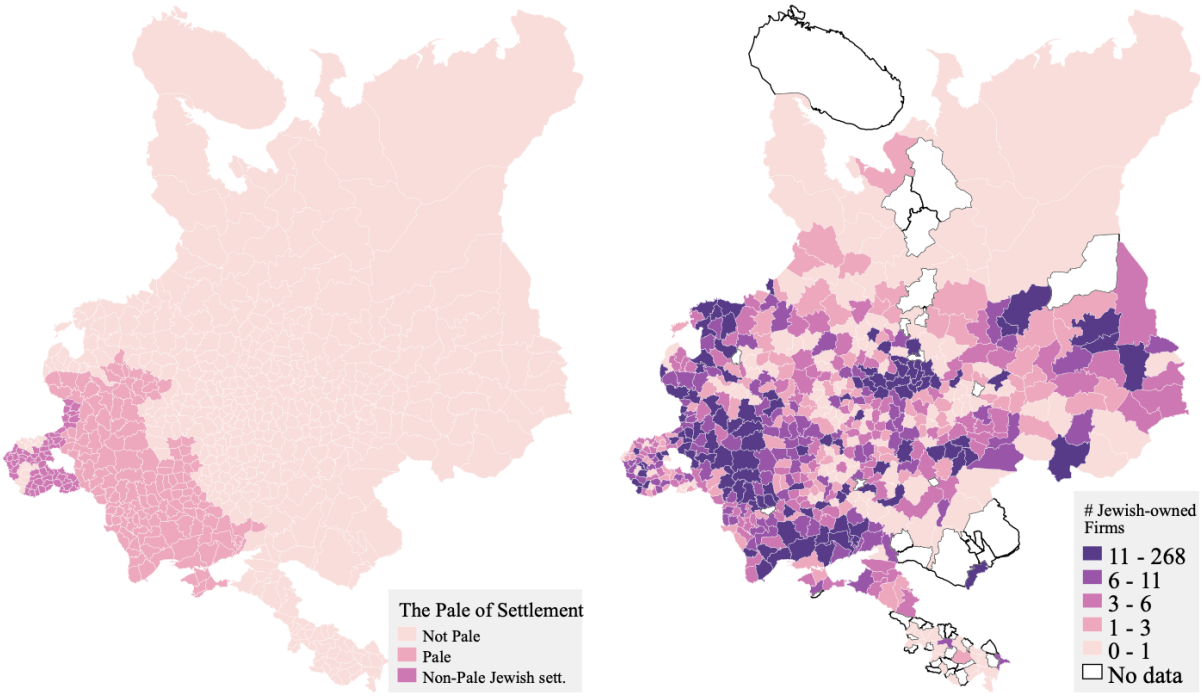
	log Revenue per worker (1)	TFP (2)	Machine Power (3)
Connected	0.091***	0.076***	0.077
	(0.025)	(0.026)	(0.052)
log Age	0.038***	0.038***	-0.013
	(0.008)	(0.009)	(0.021)
log Num. Empl.	0.040**	-0.034	1.048***
	(0.020)	(0.022)	(0.059)
Factory is located in a city	0.127***	0.140***	0.076
	(0.040)	(0.038)	(0.068)
N	5,201	5,201	4,400
Mean	6.837	0.026	41.393
R-squared	0.733	0.675	
District × Sub-industry FE	✓	✓	✓

Notes: Sample limited to firms with 15 or more employees. TFP is calculated as a residual after regressing log Revenue per worker on log Number of workers and log Machine power (+1). Connected ethnic groups are defined according to the algorithm described in Section 3.2.

C Jewish entrepreneurs

C.1 Jews in the Pale

We explore the spatial distribution of Jewish owners with respect to the pale of settlement. Large number of the Jewish-owned factories fell in the Pale of Settlement, but the distribution was indeed wider, as many Jews could live outside of the pale, especially if they were richer.



(a) Pale of Settlement (b) # factories owned by Jews

Figure C3: Pale of Settlement and Jewish Factories

Notes: Source of the shapefile: Kessler and Markevich (2021).

In Table C3 we show that Jews inside and outside of the Pale (here defined as the official Pale + the Congress Poland Provinces) ran similar factories, but less capital-intensive ones, consistent with the idea that Jews allowed to live outside the Pale usually had to meet certain wealth requirements and therefore would have had less means to purchase machinery. Interestingly, these differences in capital did not translate into significant productivity differences, suggesting that Jews in the pale perhaps faced less discrimination from outsiders when living in the pale.

Table C3: Jewish-owned firms within and outside of the Pale of Settlement

	Log Revenue per Worker	TFP	Machine Power
	(1)	(2)	(3)
Jews in Pale	0.068	0.059	-0.149**
	(0.059)	(0.054)	(0.067)
log Age	0.032***	0.030**	-0.008
	(0.012)	(0.012)	(0.022)
log Num. Empl.	0.108***	0.089***	0.874***
	(0.024)	(0.024)	(0.032)
Factory is located in a city	0.325***	0.306***	0.280***
	(0.049)	(0.047)	(0.097)
Observations	4,616	4,616	4,993
Mean Dependent Variable	6.910	0.051	21.123
R-squared	0.414	0.362	
Sub-industry FE	✓	✓	✓
Controls	✓	✓	✓

Notes: Robust standard errors clustered at the district level. "Jews in Pale" is a binary variable equal to one if a firm was owned by a Jewish entrepreneur and was located within the Pale of Settlement. TFP is residual in a regression of log revenue per worker on log number of workers and log total machine power(+1). Jewish ethnic origin is defined according to the algorithm described in Section 3.2.

C.2 Robustness to excluding Jewish owners

Jewish entrepreneurs were crucial in the economy of the Russian Empire. They operated 5,492 (34.6%) of all private enterprises. However, using the firms we classify as Jewish-owned could be problematic for two reasons. First is that the Russian Empire had a history of anti-semitic policies and outright violence, such as Pogroms. Therefore, Jewish entrepreneurs may have faced more administrative and social challenges while running their firms than other entrepreneurs. Second, our classification counts as Jews all Russian last names that were used as both Jewish and Russian. Therefore, we may be incorrectly assigning some of the Russian Entrepreneurs to our Connected definition, thus biasing our results down. We replicate Table 3, dropping all observations we classify as Jewish-owned. Indeed, all the results hold up in this sample.

Table C4: Connected ownership and productivity (subsample without Jewish firms owners)

	log Revenue per worker	TFP	Machine Power	log Revenue per worker	TFP	Machine Power
	(1)	(2)	(3)	(4)	(5)	(6)
Connected	0.119***	0.103***	0.075			
	(0.038)	(0.034)	(0.074)			
German				0.149***	0.120***	0.001
				(0.046)	(0.042)	(0.209)
Jewish						
Other Connected				0.108***	0.097***	0.104
				(0.039)	(0.035)	(0.094)
log Age	0.044***	0.045***	-0.009	0.044***	0.045***	-0.008
	(0.009)	(0.009)	(0.019)	(0.009)	(0.009)	(0.018)
log Num. Empl.	0.089***	0.065**	0.971***	0.089***	0.065**	0.972***
	(0.033)	(0.032)	(0.059)	(0.033)	(0.032)	(0.062)
Factory is located in a city	0.323***	0.314***	0.033	0.324***	0.315***	0.030
	(0.066)	(0.056)	(0.077)	(0.066)	(0.057)	(0.078)
Noble last name	-0.028	-0.027	-0.064	-0.028	-0.027	-0.064
	(0.039)	(0.034)	(0.092)	(0.039)	(0.034)	(0.091)
Observations	6,566	6,566	5,815	6,566	6,566	5,815
Mean Dependent Variable	6.819	-0.051	25.888	6.819	-0.051	25.888
R-squared	0.682	0.642		0.682	0.642	
District × Sub-industry FE	✓	✓	✓	✓	✓	✓

Notes: Robust standard errors clustered at the district level. The sample is limited to the firms with non-Jewish-classified owners. Refer to Table 3 for details on outcome variables and controls.

C.3 Jewish Name Index by Abramitzky et al. (2020)

Abramitzky et al. (2020) create a Jewish Name Index for various US Censuses, based on the percentage of individuals speaking Yiddish with a certain combination of first and last names. We use their US data of last names and assigned "Jewishness" probabilities to train our data on Jewishness of the last names in the 1894 Manufacturing Census. Because we were looking for a lower bound on Jewish counts, we used the most conservative approach. We use authors' suggested cutoff of 0.8 Jewishness probability of a last name to categorize their US data as Jewish versus not. We then use a machine learning algorithm (based on Logistic Regression),

using their data as a training sample, and applying to our last names. Out of the 9,705 total last names, only 701 (7.3%) are considered Jewish by this algorithm. This is much lower than the yield of our main classification method, the Dictionary of Jewish last names, at 27%. This algorithm, however, clearly undercounts Jewish last names: while last names such as "Abramov" are correctly identified as Jewish, last names "Abramovskii" and "Abramovich" are not, as, most likely, these Eastern European last name structures were not as common in the US in the first half of the 20th century. Further, 194 last names this algorithm considers Jewish do not appear in the Dictionary, so we treat these as non-Jewish. Thus, we are left with 507 unique Jewish last names in our data, corresponding to 1,340 (8.25%) firms.

We then re-ran our ethnicity-assignment algorithm described in the main body, on the non-Jewish portion of our sample. First, we explore what happened to the last names that were listed in the Jewish Dictionary but were not identified as Jewish by this algorithm. There were 4,299 such firms. 1,826 were now considered Other Connected; 1,524 were now considered Russian; 918 were considered German; only 31 were considered Eastern.

Next, we reproduce our main findings (Table 3) in Table C5. Reassuringly, while smaller, all the coefficients on Connected are positive (Columns 1-3). In addition, all the coefficients on German are also positive, and significant for revenue per worker and TFP. The coefficients on Jewish remain large and significant for revenue per worker and TFP. The coefficients for Other Connected are positive but lose statistical significance. These results reassure us that our classification of Jewish last names does not alter the takeaways of our findings, and validate our main measure using alternative data source.

Table C5: Alternative measurement of Jewish surnames

	log Revenue per worker	TFP	Machine Power	log Revenue per worker	TFP	Machine Power
	(1)	(2)	(3)	(4)	(5)	(6)
Connected	0.065***	0.063**	0.052			
	(0.025)	(0.026)	(0.046)			
German				0.091***	0.081**	0.043
				(0.035)	(0.036)	(0.123)
Jewish				0.085**	0.099**	-0.083
				(0.039)	(0.040)	(0.057)
Other Connected				0.047	0.039	0.098
				(0.029)	(0.029)	(0.061)
log Age	0.043***	0.044***	0.001	0.040***	0.041***	-0.001
	(0.007)	(0.007)	(0.015)	(0.007)	(0.008)	(0.014)
Num. empl.	0.072***	0.051**	0.926***	0.074***	0.053**	0.929***
	(0.022)	(0.025)	(0.046)	(0.022)	(0.025)	(0.045)
Factory is located in a city	0.269***	0.256***	0.053	0.265***	0.250***	0.052
	(0.049)	(0.045)	(0.054)	(0.049)	(0.046)	(0.055)
noble	-0.029	-0.025	0.009	-0.029	-0.027	0.024
	(0.026)	(0.026)	(0.059)	(0.026)	(0.026)	(0.058)
Observations	10,589	10,589	9,375	10,222	10,222	9,012
Mean Dependent Variable	6.850	-0.015	25.791	6.840	-0.020	26.264
R-squared	0.671	0.629		0.673	0.632	
District × Sub-industry FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓

Notes: Robust standard errors clustered at the district level. Jewish classification altered to use Abramitzky et al. (2020)'s Index. See Table 3 for details on outcome variables and controls.

Further, we again map the Jewish-owned factories by district, using this new classification method. We did this to confirm that even using this conservative estimate, that is based on more "definitely-Jewish" and fewer mixed-use last names, we still observe the geographic dispersion of Jewish-owned factories we saw in C3. In Figure C4, we see that this is in fact the case, and the concentration in the Pale of Settlement is even lower. This once again, gives us confidence in using our original method.

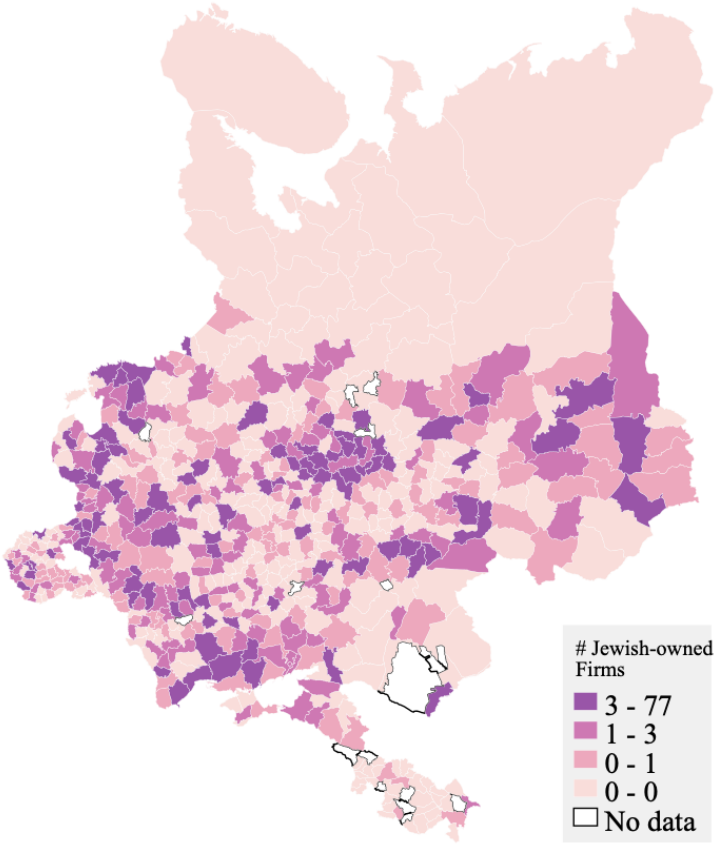


Figure C4: Number of factories owned by Jewish entrepreneurs using Jewish Name Index method from Abramitzky et al. (2020).

D Chicago World's Fair

Table D6 shows that firms at the Chicago World's Fair had higher baseline productivity measures than the firms that did not participate.

Table D6: Productivity of Russian firms at the 1893 Chicago World Fair

	log Revenue per worker	TFP	Machine Power
	(1)	(2)	(3)
Participated in Fair	0.224**	0.167	0.263**
	(0.101)	(0.103)	(0.128)
log Age	0.044***	0.044***	0.003
	(0.007)	(0.007)	(0.014)
log Num. Empl.	0.071***	0.051**	0.920***
	(0.022)	(0.025)	(0.046)
Factory is located in a city	0.273***	0.259***	0.056
	(0.049)	(0.045)	(0.054)
Noble last name	-0.032	-0.028	0.012
	(0.026)	(0.026)	(0.059)
Observations	10,714	10,714	9,501
Mean Dependent Variable, Fair = 0	6.846	-0.020	25.209
R-squared	0.669	0.628	
District × Sub-industry FE	✓	✓	✓
Controls	✓	✓	✓

Notes: Standard errors clustered at the district level. Participated in the Fair is a binary variable equal to one if a firm was matched to the Chicago World's Fair directory. All other components of the specification same as in Table 3.

E German advantage by industry: additional evidence

E.1 German and non-German productivity premium by industry

	Log Revenue Per Worker										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Animal	Chemical	Cotton	Flax	Foods	Metals & Machines	Mineral	Paper	Silk	Wood	Wool
German	0.069	0.694***	0.101	0.000	0.232*	0.150**	0.024	0.027	-0.386***	0.450**	0.020
	(0.180)	(0.093)	(0.283)	(.)	(0.121)	(0.072)	(0.132)	(0.120)	(0.041)	(0.221)	(0.092)
N	676	151	177	120	1,642	351	420	169	156	257	221
Mean	6.909	6.727	6.846	6.562	7.108	6.466	5.686	6.481	6.294	6.716	6.648
R-squared	0.668	0.812	0.492	0.487	0.660	0.604	0.634	0.669	0.443	0.666	0.630
District × Sub-industry FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

	Log Revenue Per Worker										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Animal	Chemical	Cotton	Flax	Foods	Metals & Machines	Mineral	Paper	Silk	Wood	Wool
Connected (not German)	0.137	-0.009	0.272	0.483	0.064	0.290***	0.038	0.138	-0.231	0.277	0.268*
	(0.107)	(0.140)	(0.214)	(0.377)	(0.063)	(0.092)	(0.070)	(0.120)	(0.136)	(0.176)	(0.146)
N	699	176	181	127	2,256	347	478	216	156	292	224
Mean	6.916	6.765	6.861	6.581	7.036	6.482	5.691	6.452	6.267	6.799	6.681
R-squared	0.667	0.805	0.503	0.484	0.648	0.642	0.626	0.515	0.411	0.641	0.649
District × Sub-industry FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

E.2 Stories of German entrepreneurs in the chemicals industry

Below, we recount stories of some of the German chemicals entrepreneurs who appear in the Census and whose stories we have been able to find. These examples illustrate the lived experiences behind the "connections" we describe throughout the paper.

Three Russian-born German brothers, Edward, Robert, and Wilhelm Bremme, whose father was himself an immigrant entrepreneur, were sent to Göttingen University to study Chemistry.[24] All three returned to the Russian Empire and started an essential oils and essences firm called "Brothers Bremme". In the Census, the firm appears to have been successful - it had opened in 1886, operated 290 days a year, had a steam engine, employed 25 men, and generated 45,000 rubles in revenue. This story illustrates a likely channel through which cultural connections operated - immigrants who had studied in Germany or descendants of immigrants who had left the Empire to study in Germany due to their knowledge of the language, culture, and family ties came back and used their knowledge to start companies.

Another story is of direct immigrant transplants who started a chemicals firm - Sigismund and Emil Erlenbachs. We find Sigismund later in history involved in trade with Germany during World War I, where he is identified as a Bavarian national and treated with suspicion.[25] In our data, Sigismund and Emil Erlenbachs own a Paints and Lacquer company founded in 1888, which operated 240 days a year, had a steam engine, employed 8 men and 2 boys, and generated 26,800 rubles in revenue. Thus, direct German immigrants are certainly a part of our data and explain the productivity differences.

However, Germans not only operated more productive companies but also innovated within the industry. In 1892, Max Geflinger, Pavel Emilev, and Rudolph Schmitz were the first to open a superphosphate - first chemical fertilizer - factory in the Russian Empire (Gusev, 2020). Two of the three founders had obviously German first and last names. Thus, German owners were pioneers within at least one important chemical subindustry in the Russian Empire.

[24] source: https://www.dp.ru/a/2019/08/29/Fabrichnij_aromat
[25] http://www.raruss.ru/excellent/2737-leman-gravure.html

F Human capital

Another concern with our interpretation of the results is that we may be capturing the effect of a stock of human capital. It is possible and likely that the "connected" entrepreneurs were better educated. Perhaps it was due to this superior education that they were able to run more productive firms. First, this explanation does not hold in light of our findings with the German owners and chemicals industry. However, we present another exercise – we limit the sample to districts with high literacy rates (more than 75% or 6% of the sample) as captured by the 1897 population census. Table F7 shows that even within such a small and positively selected sample, the productivity premia for connected firms remain and are even substantially higher than the baseline results.

Table F7: Literacy and Productivity Measures; districts with more than 75% literacy

	log Revenue per worker (1)	TFP (2)	Machine Power (3)	log Revenue per worker (4)	TFP (5)	Machine Power (6)
Connected	0.523***	0.612***	0.151			
	(0.147)	(0.147)	(0.205)			
German				0.533***	0.630***	0.113
				(0.144)	(0.148)	(0.197)
Jewish				0.533***	0.619***	0.217
				(0.156)	(0.158)	(0.224)
Other Connected				0.477***	0.570***	-0.083
				(0.138)	(0.125)	(0.174)
Observations	662	662	725	662	662	725
Mean Dependent Variable	7.257	0.225	13.865	7.257	0.225	13.865
R-squared	0.709	0.681		0.709	0.681	
District × Sub-industry FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓

Notes: Robust standard errors clustered at the district level. The sample is limited to the firms in districts with more than 75% literacy. Refer to Table 3 for details on outcome variables and controls.

G Distance to Europe and ease of communication

Establishing and maintaining ethnic connections, especially at a time of high transportation costs, would have been positively correlated with physical distance to Europe. Indeed, many ethnic groups we study, such as Poles, originally had connections with Western Europe due to their geographic location. To evaluate how distance and connectedness interact in our setting, we calculate Euclidean distances from county centroids to the closest point on the border of the Empire with Europe. We then interact this distance measure with our connected dummy. Table G8 presents these results. The effect of distance is small and statistically insignificant.

Table G8: Complementarities of connectedness and distance to Europe

	(1) log Revenue per worker	(2) TFP	(3) Machine Power
Connected	0.085***	0.092***	0.002
	(0.033)	(0.034)	(0.036)
Connected * Log Distance	0.004	-0.003	0.031
	(0.015)	(0.015)	(0.021)
log Age	0.043***	0.043***	0.002
	(0.007)	(0.007)	(0.014)
log Number of employees	0.075***	0.054**	0.925***
	(0.022)	(0.024)	(0.045)
Factory is located in a city	0.275***	0.260***	0.060
	(0.048)	(0.045)	(0.055)
Noble last name	-0.033	-0.027	0.001
	(0.026)	(0.025)	(0.058)
Observations	10,729	10,729	9,525
Mean Dependent Variable	6.851	-0.016	25.779
R-squared	0.669	0.628	
District × Sub-industry FE	✓	✓	✓
Controls	✓	✓	✓

Notes: Robust standard errors clustered at the District level. Distance is calculated as the euclidean distance of the district in which the factory is located and the closest point on the Russian Empire's border with Europe. All other definitions as in Table 3.

However, physical distance may not capture the ease of "connection", especially in a country as vast as the Russian Empire. Connections, instead, would have been facilitated by telegraph lines, railroads, and postal systems. All these existed in large cities.

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