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

Tamar Matiashvili[1] and Timur Natkhov[2]

[1]Stanford University
[2]Higher School of Economics

June 25, 2024

Abstract

What factors facilitate the adoption of advanced technologies in developing economies? This paper examines the role of ethnic connections in the diffusion of innovation in the context of industrialization. We combine machine learning and heuristic methods with a surnames dictionary to assign probable ethnicities to owners of nearly 16,000 industrial firms of the 1894 Manufacturing Census of the Russian Empire. We compare firms owned by entrepreneurs with cultural connections to Europe (Germans, Jews, Poles, etc.) with firms owned by Russians or indigenous minorities of the Empire. We find that "connected" firms exhibited higher productivity, utilized modern machinery, and implemented advanced management practices, such as sharing ownership with partners, employing women, and operating on a more regular basis. We argue that these advantages stemmed from superior knowledge of production techniques acquired from the leading industrial countries. We establish this mechanism by showing, among others, that even within a subset of positively selected firms that participated in the Chicago World's Fair in 1893, "connected" firms were significantly more likely to trade with Europe. We also show that German entrepreneurs in the Russian Empire had the largest productivity advantage in chemicals – Germany's leading industry in the late 19th century. Our findings highlight the importance of cultural links in the diffusion of Industrial Enlightenment from the European core to the periphery.

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

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

*Corresponding author: Tamar Matiashvili. E-mail: tamrim@stanford.edu. We are grateful to Ran Abramitzky, Liran Einav, Pete Klenow, and Steve Nafziger for their invaluable feedback. We also thank the participants of various Stanford Economics Department workshops, 2023 Summer Workshop in the Economic History and Historical Political Economy of Eurasia, Asia-Pacific Economic and Business History Conference 2024, and ASREC Chapman 2024.

1 Introduction

What factors facilitate the adoption of advanced technologies in developing economies? 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 establishments in the late Russian Empire — a typical example of a late-industrializing economy. We show that entrepreneurs' cultural connections with the technological frontier facilitate the adoption of advanced technologies, both at extensive and intensive margins, increasing firms' productivity. These "connected" firms then serve as role models for local entrepreneurs inducing spillovers of productivity and capital innovation.

We employ the uniquely detailed manufacturing census of about 16,000 industrial establishments conducted by the Ministry of Finance of the Russian Empire in 1894 (Ministry of Finance, 1897).[3]. The census was taken at an opportune time - at the end of the 19th century, the Russian Empire was rapidly industrializing, allowing us to study the economy in its transition. The census includes information on a firm's name, location, employment, types and amount of machinery, industry, revenue, and other variables. Factory names include owners' last names, which allow us to identify the likely ethnicities of firm owners. We employ sources like "A Dictionary of Jewish Surnames from the Russian Empire" (Beider, 2008) and a machine learning algorithm to assign a most likely ethnicity to each firm owner. We then classify them into one of the five different groups: Russians, Germans, Jews, Other Westerners (Poles, Lithuanians, etc.), and Eastern minorities. Of these five groups we regard Germans, Jews and Other Westerners as culturally "connected" to Europe, whereas Russians and Eastern minorities as "non-connected".

We show that "connected" entrepreneurs played a major role in the adoption of industrial machinery and advanced management practices. In particular, we find that firms owned by "connected"

[1]See Comin and Mestieri (2018) and Comin and Hobijn (2010) for relatively recent studies, and Keller (2004) for less up to date 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 for more detailed description of the data. We thank Amanda Gregg for kindly sharing the digitized version of the Census.

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 that ran on modern types of fuel such as steam, oil and gas. They also utilized advanced management practices by sharing ownership with partners, employing women, and operating on a more regular basis. We focus on private firms instead of corporations, ensuring that the advantages we document did not stem from access to the stock market, protection of limited liability, or other exclusive rights.

We argue that the main source of higher productivity of the "connected" entrepreneurs was their knowledge of modern production techniques and advanced management practices. This knowledge was mainly acquired through cultural links to European countries. We test this hypothesis using several different approaches. First, we digitize data for all Russian firms that participated in the 1893 Chicago World's Fair – an exhibition of the technological advancements of leading industrial nations in the late 19th century. We find that, even among these positively selected firms, differences in owners' cultural origins affected the extent of their connections to Europe. "Connected" firms were significantly more likely to trade with Western Europe and benefit from the know-how exchange with advanced nations.

Second, we identify industries in which Germany, one of the leading industrial nations at the time, attained comparative advantage, and see whether entrepreneurs of German origin in the Russian Empire also had an advantage in the same industries. Estimating the regression models separately for each industry, we find that German-owned firms had the largest productivity advantage in the chemicals industry – about 80% higher revenue per worker than Russian-owned firms. This directly corresponded to Germany's world ascendance in the chemicals industry in the late 19th century. 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 all patents issued in the Russian Empire in 1892-1896. We find that of all the patents issued to non-foreigners, only 24% had been issued to Russians and Eastern minorities, while the remaining had been issued to individuals with Western surnames. Thus, innovation in the Russian Empire appears to have been largely driven by the "connected" groups.

To further strengthen our argument, we examine the role of local spillovers. Presumably, a significant share of technology diffusion happens at the local level when less productive firms try to emulate a domestic "role model" in their industry. We then ask if higher exposure to "connected" firms facilitates technology adoption for "non-connected" firms operating in the same market. We find that "non-connected" firms exposed to a higher share of "connected" firms in a given industry and district were indeed more productive. Out of all productivity measures, the largest coefficient is for revenue TFP, implying that spillovers of know-how and management practices were probably more consequential than the adoption of machines. This result provides evidence of knowledge diffusion from "connected" to "non-connected" firms at the local level.

Finally, ease of communication and transportation to Europe could matter in enabling the cultural connections. We find that the "connected" groups benefited more if they were located in one of the 17 largest cities (population $>$ 100,000 in 1897) in the Russian Empire. These largest cities would have provided the communication channels necessary to maintain connections with Europe. Additionally, we find that "connected" firms closer to the European border also benefitted from the shortened distance, but these results are not precise.

We conduct a set of additional empirical exercises to rule out competing explanations. An important threat to the proposed mechanism is the fact that firm owners with Western surnames may have started their businesses with significantly larger amount of capital. We address this concern by showing that the productivity premium for "connected" firms existed even within the sub-sample of firms without any machinery, namely without initial capital investments. We further try to rule out the human capital effect by focusing on a small subset of highly literate districts, and again find similar results. We also show that there did not seem to be significant ethnic network effects – being surrounded by same-industry upstream and downstream firms owned by individuals of the same ethnicity did not confer a productivity premium, and if anything, was associated with lower performance. Finally, we rule out in-group effects for the Western groups – the productivity premium of "connected" firms was just as strong when located in districts with ethnic Russian majority as in districts with non-Russian majority.

We contribute to several strands of literature. First is the literature on the determinants of technology diffusion. Spolaore and Wacziarg (2009, 2014) show that cultural barriers, measured by genetic distance to the technological frontier, explain a large portion of the productivity gap in a cross-section of countries. Similarly, Ashraf and Galor (2011) show that cultural isolation precluded the adoption of new technologies, delaying the onset of industrialization. Historically, the diffusion of industrial knowledge across Europe was associated with the presence of upper-tail human capital (Squicciarini and Voigtländer, 2015), scientific societies (Cinnirella et al., 2022), 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 also facilitate technology diffusion, especially for an economy distant from the frontier in terms of institutions, cultural norms, and accumulated human capital.

Second, we contribute to the literature on the determinants of firm productivity (Syverson, 2011). One of the main factors of productivity variation across firms is management quality. For example, Bloom et al. (2019) estimate that differences in management practices account for 20% of differences in productivity in US plants, while Bloom et al. (2020) find that management interventions had long-term productivity-boosting effects on Indian weaving firms. Giorcelli (2019), uses a quasi-experiment that allowed some Italian firms to train their management staff in the United States, receive technological transfers, or both as a part of the Marshall Plan. She finds that the performance of firms that had the management training was higher for at least fifteen years after the intervention, while receiving new machines had only a short-run benefit. We complement this result, showing that firms with advanced management practices may induce positive spillovers for local firms without cultural connections to the technological frontier.

Third, in terms of the measurement techniques, our paper contributes to a large body of literature focused on using names to infer likely ethnic routes. Fryer and Levitt (2004) first introduced the index of name distinctiveness to identify names belonging to different racial groups in the United States. Abramitzky et al. (2014) adopted this method to evaluate foreignness of names in the United States. Fouka (2020) narrowed it down to create a German Name Index to identify German-sounding names in the United States Censuses. These indices used correlations between last name frequencies and race or national origin to identify likely name origins. In a similar spirit but a new method, Abramitzky et al. (2020) used association of names with spoken language (Yiddish), to determine the likelihood of first and last names being of a certain ethnic origin (Jewish). These indices all rely on variables beyond the last name to assign probabilities. We created a new method of ethnicity classification that would work in multi-ethnic societies with surnames as the only input.

Finally, we contribute to the growing empirical literature on the industrial history of the Russian Empire. Gregg (2020) demonstrates a strong association between corporate form and productivity, and Gregg and Nafziger (2019, 2024) show that Russian corporations demonstrated dynamism and flexible financial strategies, leading to greater investment in new technologies, despite operating in rigid institutional environment. Gregg and Matiashvili (2022) show the role of factory operating time with regard to industrialization and growth. We show that cultural and ethnic diversity played an important role in the decisions leading to many of these operating decisions, such as working days and organizational form (such as partnerships), which contributed to the Russian Empire's industrialization and economic progress in the 19th century. As Mokyr (forthcoming) suggests, diversity can benefit economic progress in states with sufficiently well-developed pluralist institutions, but can be detrimental in other, less-developed contexts. The institutions of the Russian Empire, backward as they may have been as discriminatory to groups such as Jews, seem to have still supported economic progress by allowing diverse groups to pursue entrepreneurship and innovate.

In the following section, we introduce the dataset and describe the measurement of our key variable – ethnic origin of a firm owner. We then evaluate how differences in productivity between firms reflect owners cultural connections with the technological frontier. In the following sections, we provide evidence for possible mechanisms of this correlation, and evaluate alternative explanations for the observed patterns.

2 Data and measurement

2.1 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 includes only manufacturing firms and thus excludes mining, farming, fishing and other non-manufacturing industries. A factory was included in the census if at least one of the following conditions were met: it had at least 15 employees or it had a steam engine, a steam boiler, or other mechanical device. The purpose of the census was to inform the central government about the industrialization of the Empire. The census did not inform tax collections, so the usual concern of under-reporting in such surveys does not apply to these data. The census includes a large number of measures describing a factory's operation: owner's first and last names, location, types of products the firm produced, number of employees by sex and age groups, number and types of machines the firm employed, horsepower per machine, total revenue, and some others.

Exploring one firm in detail allows to understand the data better. A firm called "Solitermann" was probably the closest to a representative firm in the Census. It was located in the city of Bratslav in the Podolsk province and operated in the Flour sub-industry within the Foods industry. It had one water wheel, which generated 75 horsepower in energy. It employed 13 workers (no women or children), was founded in 1888, operated for 240 days in 1894, and generated 65,202 rubles in revenue. For now, we focus on the 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. A median firm in the Census was somewhat similar to "Solitermann". It employed 13 people (usually only men) and was slightly more likely to be in a rural area. It operated in a relatively simple industry like textiles or food processing, and had two horsepower units coming from a steam engine. It was open for 240 days a year (suggesting it was closed for the summer), and generated 15,000 rubles in revenue (see Table 1 for summary statistics).

Jewish surnames. We use "A Dictionary of Jewish Surnames from the Russian Empire" by Beider (2008), which includes all last names ever used by Jews of the Russian Empire, for a total of about 74,000 last names.[4] We use this source to discriminate between 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 names' structure.

1893 Chicago World's Columbian Exposition. The Russian Empire presented 1,022 exhibits at the

[4]We thank the author, Alexander Beider, who kindly shared the database in the Excel format.

1893 World's Columbian Exposition held in Chicago. The crown financed the transportation of exhibits, which included art, inventions, and, notably, factory output and machines. The Ministry of Finance issued a catalog of all Russian exhibits, government- or privately run (Ministry of Finance, 1893). If an exhibitor was representing a factory, a short blurb describing a 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, the source of various materials, 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 a 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 the data on patents to present descriptive evidence on differences in patenting behavior between "connected" and non-connected firms. Patents had been issued in the Russian Empire since 1812. Like in Western Europe and the US, inventors would apply for patents on 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 the patents issued in the years 1892-1896 from the official source published by the Department of Trade and Manufacturing (1897). The list includes the assignee's name, the nature of the patent, the year of the grant, and the patent term. Additionally, it has information on whether the assignee is a foreign national.

1897 Population Census and other sources. 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 districts by their ethnic labor and customer base.

2.2 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 three broad categories: 1) Russians; 2) Eastern minorities (Tatars, indigenous people of the Caucasus, etc.); 3) Connected – ethnic groups with a large number of their representatives in European countries, such as Germans, Jews, and Poles. Acknowledging that the assignment can never be done perfectly, we combine several complementary approaches to construct the measure.

First, we use the comprehensive dictionary of all Jewish surnames in the Russian Empire (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 differentiate between Jewish and German entrepreneurs since these groups faced different legal conditions in the Russian Empire. This differentiation 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 for two reasons. First, the proportion of such mixed-use surnames is small. Second, 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 simply shrinking the German sub-sample. In either case, we are not inflating the coefficient on Connected groups in our regressions. The matching between the dictionary and the manufacturing census shows that 27% of the unique surnames in the census were Jewish.[5]

Having separated Jewish surnames, we are left with 7,119 unique non-Jewish surnames in the census. We then use the fact that several ethnicities in the Empire had common last name endings to heuristically separate out specific ethnic groups - e.g., "*-ko*" for Ukrainian, "*-ok*" for Belarussian, "*-shvili*" for Georgian, etc.

We then use surname endings *-ov(ova), -ev(eva)*, and *-in(ina)* to separate Russian-sounding surnames from non-Russian-sounding surnames. Within the Russian-sounding part, we trained a logistic regression machine learning algorithm that produced high accuracy (94%) separation of "genuinely" Russian surnames from the "Russified" ones (ethnic minorities who habitually changed their surnames to assimilate with the Russian majority).

The rest of the sample consists of non-Russian-sounding surnames, which include German, Polish,

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

Baltic peoples', and other Western European surnames. The goal was then to separate German-sounding surnames. Again, two human trainers manually classified a part of the sub-sample, and the machine-learning algorithm was then applied to the remaining list. Accuracy was realistically high – more than 73%.[6] The rest of the non-Russian-sounding sub-sample (apart from Germans) we classified as "Other Connected" groups.[7]

Thus, the whole sample was divided into five mutually exclusive groups: Jewish firms (34%), Russian firms (33%), 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. 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). Second, 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.

2.3 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%.

[6] Accuracy rates between 70 and 90% are considered good.

[7] 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. Currently, we "upcode" these firms against our main hypothesis, such that all firms with at least one Connected owner are considered Connected. Similarly, every firm with no Connected owner and at least one Russian owner is considered Russian.

Table 1: Summary statistics

	Mean	Median	Std. dev.	N
Firm ownership				
Connected firms	0.65	1	0.48	10,580
German	0.12	0	0.32	1,911
Jewish	0.35	0	0.48	5,653
Other Connected	0.18	0	0.39	3,016
Non-Connected firms	0.35	0	0.48	5,717
Russian	0.34	0	0.47	5,521
Eastern minorities	0.01	0	0.11	196
Productivity measures				
Revenue per worker, rubles	1745	975	2969	13,688
Revenue TFP	-0.013	0	1.1	13,869
Machine power, horsepower	20.4	2	76.14	15,880
Has at least one machine, %	58	100	49	16,297
Has at least steam engine %	33	0	47	16,297
Other firm's characteristics				
Number of employees	39.6	13	114.9	16,297
Women employees, %	7.5	0	17	15,931
Age of a firm, years	19.5	14	20.2	13,690
Urban location, %	43.5	0	49.6	16,297

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 2.2.

An average firm employed about 40 workers, had one horsepower per worker, and generated about 1,700 rubles of revenue per year. 58% of firms had at least one machine, and for 33%, the machine was the steam engine. About 44% were located in urban areas. Machine power was heterogeneous across firms, with a mean (20.4) and median (2) far apart, particularly due to many firms with no machine power.[8]

In addition to revenue per worker and machine power, we use Revenue TFP as our productivity measure. We define Revenue TFP (TFP hereafter) as the residual of the simple Cobb-Douglas production function, with log capital defined as the log of a factory's machine power and log labor defined as the log of the total number of employees. Note here that we face a common challenge in industrial literature, where we observe factory-level revenues but not quantities produced. Thus, our definition of TFP represents revenue (TFPR) rather than output (TFPQ) total factor productivity.

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

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 (2014a) 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 will likely understate true productivity differences based on TFPQ.

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

Table 2: Industries by ownership

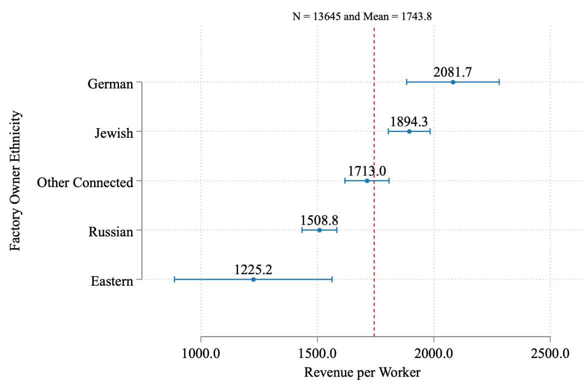
Industry	Russian	German	Jewish	Other Connected	Eastern
All	0.34	0.12	0.35	0.19	0.01
Animal	0.51	0.05	0.35	0.08	0.01
Chemical	0.38	0.10	0.37	0.14	0.02
Cotton	0.52	0.07	0.32	0.07	0.03
Flax	0.57	0.01	0.36	0.05	0.01
Foods	0.30	0.13	0.32	0.25	0.01
Metals and Machines	0.28	0.17	0.35	0.19	0.01
Mineral	0.37	0.11	0.35	0.16	0.01
Mixed Materials	0.34	0.13	0.38	0.14	0.01
Paper	0.26	0.13	0.39	0.21	0.02
Silk	0.53	0.04	0.26	0.05	0.12
Wood	0.30	0.13	0.37	0.18	0.01
Wool	0.20	0.20	0.44	0.16	0.00

Next, we look at the differences in productivity measures across different ethnic groups. Figure 1

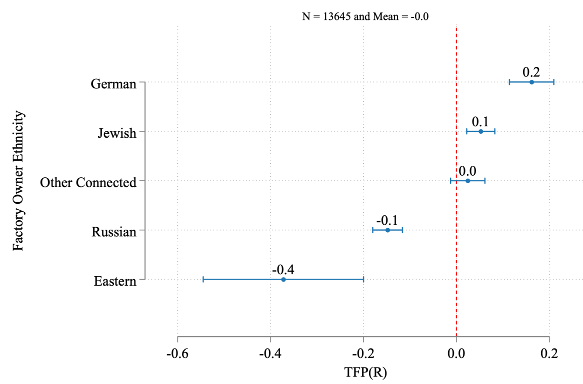
[9]between-country variation in how much TFPR responds to rises in TFPQ varies from as low as 10 percent in the US to 50-60 percent in Mexico (Hsieh and Klenow, 2014a).

[10]We use industry classification as presented in the Manufacturing Census. The Census also reports sub-industries (or primary activities) for each firm. On average, each of the 12 industries had about 40 primary activities. For instance, 55% of the firms in the Paper industry reported their primary activity as Typography, while the second most common activity, 11%, was Paper Production. For this reason, we introduce primary activity fixed effects in addition to industry fixed effects in the regression analysis to make sure we are comparing firms that are operating in the same markets.

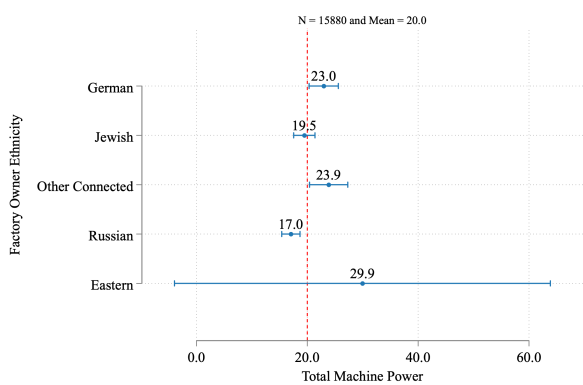
plots firms' characteristics for each of the five groups we identified with our ethnicity assignment algorithm. We observe that German firms were leaders in revenue per worker, TFP and the number of working days per year. Jewish firms were significantly higher than average in revenue per worker, TFP, and working days, but not in machine power. Other Connected firms (Polish, Baltic peoples) were higher than average in machine power and close to the average in revenue per worker, total factor productivity, 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 A2 for spatial distributions of connected firms and TFP). In the following section, we assess these patterns using regression analysis.



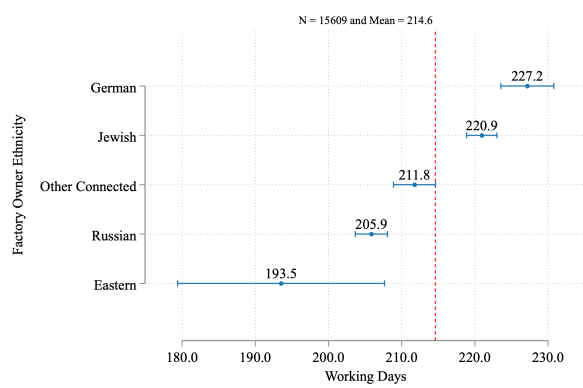
(a) Revenue per worker



(b) TFP



(c) Machine power



(d) Working days

Figure 1: Outcomes by ethnic groups

Notes: Vertical red line represent 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 (+1). Ethnic groups are defined as probable ethnic identity of the firm's owner according to the algorithm described in Section 2.2.

3 Empirical strategy and results

3.1 Empirical strategy

Our baseline estimation is an OLS model of the form:

$$Y_{idj} = \alpha_{idj} + \beta * \text{Connected}_{idj} + \gamma_d + \delta_j + \nu X_{idj} + \epsilon_{idj} \quad (1)$$

where Y_{idj} are various outcomes, such as log revenue per worker, TFP, log machine power per worker, for firm i in district d and primary activity j. $Connected_{idj}$ is a dummy for a firm with owners connected to European countries. In an alternative specification, we subdivide Connected firms into components, namely Germans, Jews and Other Connected to estimate separate coefficients for each group. In these cases, we use three dummies – Germans, Jews and Other Connected – as explanatory variables. In both specifications, however, the basis for comparison is the same – firms owned by ethnic Russians and Eastern minorities. All specifications include district-level fixed effects, γ_d, and industry and primary activity fixed effects, δ_j, to compare firms that operate in the same markets.

In all specifications, we control for the logarithm of factory age, number of employees, a dummy for urban location, and whether a last name was included in the General Armorial of the Noble Families of the Russian Empire by 1917 (Russian Noble Assembly, 1917), all of which are represented by vector X_{idj}. Controlling for factory age allows to mitigate potential concern that younger factories would be more likely to be connected and to invest in a newer technology than incumbents, due to technological path dependence for older factories (Hsieh and Klenow, 2014b; Hornbeck et al., 2024). Controlling for the number of employees ensures that the sheer differences in scale of employment are not responsible for Connected firms' advantage; we do not have a prior on this variable. Controlling for urban location allows us to mitigate agglomeration effects, access to larger labor markets, and larger potential demand for firm's products, all of which might be correlated with the Connected status. Finally, controlling for whether a last name was associated with nobility could ameliorate differences in starting capital. The following subsections present the results.

3.2 Productivity measures

Table 3 presents the main results for firms' productivity measures as dependent variables. In columns 1-3 we compare Connected firms with the rest of firms in our sample. Connected firms had higher revenue per worker, higher total factor productivity, and more machine power. The economic magnitude of the ownership effect is substantial – connected firms had, on average, about 8% higher revenue per worker, about 6% higher total factor productivity, and about 8% more machine power.

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. While the coefficients do not attain 5% significance for any groups for machine power, the coefficient for the Jewish owners is sizably smaller than the other groups, whose coefficient is large but imprecisely estimated. Thus, their productivity premium may have stemmed from more efficient factor allocation or managerial practices. Other Connected groups (Poles, etc.) had a smaller advantage overall, but the coefficients are still positive in all specifications.

The magnitude of the coefficients on revenue per worker and TFP is highest for the German- and Jewish-owned firms, suggesting that the advantage of the Connected firms, documented in columns 1-3, is mostly driven by these two subgroups. Overall, the results provide strong statistical evidence on the importance of an owner's cultural background for a firm's productivity. We further test the robustness of these estimates to several specification and sample choices: (1) only looking at firms with 15+ employees (Table B1); (2) dropping Jewish-owned firms (Table C3); (3) separating Russian-sounding and non-Russian sounding Jewish owners (Table C4). In the latter exercise, we find the entire Jewish advantage stems entirely from non-Russian sounding Jews, who would be more likely to have connections with Western European Jewish diasporas, strengthening our cultural connection argument.[11]

[11] In Appendix C, we explore the spatial distribution of Jewish-owned firms (pale of settlement). We also use an alternative Jewish name assignment mechanism used by Abramitzky et al. (2020) in the US context.

Table 3: Connected firms and productivity

	log Revenue per worker (1)	TFP (2)	Machine Power (3)	log Revenue per worker (4)	TFP (5)	Machine Power (6)
Connected	0.084***	0.072***	0.079*			
	(0.023)	(0.022)	(0.043)			
German				0.122***	0.085***	0.091
				(0.032)	(0.031)	(0.083)
Jewish				0.085***	0.079***	0.055
				(0.024)	(0.024)	(0.047)
Other Connected				0.063**	0.045*	0.123*
				(0.027)	(0.026)	(0.069)
log Age	0.046***	0.046***	-0.004	0.046***	0.046***	-0.004
	(0.007)	(0.007)	(0.013)	(0.007)	(0.007)	(0.013)
log Num. Empl.	0.068***	0.042**	0.931***	0.068***	0.043**	0.931***
	(0.017)	(0.018)	(0.030)	(0.017)	(0.018)	(0.029)
Factory is located in a city	0.194***	0.196***	-0.036	0.194***	0.196***	-0.032
	(0.034)	(0.032)	(0.048)	(0.034)	(0.032)	(0.047)
Noble last name	-0.021	-0.017	0.017	-0.021	-0.021	0.026
	(0.020)	(0.020)	(0.041)	(0.020)	(0.020)	(0.040)
Observations	13,451	13,451	14,808	13,451	13,451	14,808
Mean Depent Variable	6.851	-0.016	21.253	6.851	-0.016	21.253
R-squared	0.492	0.446		0.492	0.446	
District FE	✓	✓	✓	✓	✓	✓
Industry + Main Activity FE	✓	✓	✓	✓	✓	✓

Notes: Robust standard errors clustered at District level. The outcome variable of: Columns 1 & 3 is log revenue per worker; Columns 2 & 4 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 & 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 increases in columns 3 and 6. This is due to missing revenue data for 2,235 firms in the original source net dropped 1,066 singleton observations, with overlap between the two.

3.3 Machine types

Next, we explore sources of productivity advantage of Connected firms, testing if they were more likely to possess advanced machinery. According to the Manufacturing Census, most firms did not have any machines and exclusively employed manual labor (41%). Another 12.5%, in addition to manual labor employed animal power, usually horses. The rest of the sample had at least one mechanical device – steam engine (33%), water or wind wheel (14%), or more advanced type of machinery like locomotive, gas, kerosene, or benzine engine (11%). Only three firms possessed an electric engine – one of the most advanced industrial machines at the time. Based on this data we generate two dependent dummy variables: (1) Has at least one machine, and (2) Has at least steam engine. The first takes value 1 if a firm has any machine (46% of the sample). The second takes value 1 if a firm has 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.

Table 4 presents the estimation results. Columns 1 and 2 show that Connected firms were 1.8% more likely to employ non-human and non-animal power sources in their production process, and 2.6% more likely to have advanced machinery.

Table 4: Connected firms and machine types

	Has at least one machine (1)	Has at least Steam (2)	Has at least one machine (3)	Has at least Steam (4)
Connected	0.018**	0.026***		
	(0.008)	(0.009)		
German			0.063***	0.069***
			(0.013)	(0.013)
Jewish			0.009	0.019**
			(0.008)	(0.009)
Other Connected			0.024**	0.028**
			(0.011)	(0.011)
log Age	-0.005	-0.014***	-0.005	-0.014***
	(0.003)	(0.002)	(0.003)	(0.002)
log Num. Empl.	0.140***	0.135***	0.140***	0.135***
	(0.005)	(0.005)	(0.005)	(0.005)
Factory is located in a city	-0.025**	0.022*	-0.023*	0.024*
	(0.012)	(0.012)	(0.012)	(0.012)
N	15,673	15,673	15,673	15,673
Mean	0.463	0.436	0.463	0.436
District FE	✓	✓	✓	✓
Industry + Main Activity FE	✓	✓	✓	✓

Notes: The outcome variable of columns 1 & 3 is whether a firm owned any engine type. Columns 2 & 4 are limited to only those that used at least steam (but could not have steam, but have more advanced engine types, such as gas, petrol, electricity)

In columns 3 and 4 we again divide the Connected sample into three groups and repeat the analysis. All Connected ethnic groups were more likely to employ modern technology. The results for Jewish firms are intriguing. As we show above, Jewish firms were not more likely to have more machine power per worker and, as shown in column 3, did not seem more likely to have machines, but the machine power they did have seems to have come from more advanced sources, such as steam. These findings confirm our hypothesis that Connected owners adopted modern technology at higher rates than non-Connected firms.

3.4 Management practices

Differences in productivity could also stem from variations in management practices. Management practices is a blanket term that refers to decisions not directly related to the amount of capital and labor involved in production. Below, we investigate a few possible measures that can be attributed to management practices.

One facet of industrialization in the Russian Empire was the rising employment of women, which was previously largely limited to home production and agriculture.[12] The manufacturing census allows us to determine whether a firm hired female labor, and the share of women among the firm employees. The third measure of management practices is the number of days per year that a factory operated – establishments that stayed open more days per year left capital idle for less time and generally resembled the industrial factory-like operation more than seasonal manufacturing firms did. They also seemingly succeeded in retaining labor through agricultural high seasons. [13] Finally, we explore whether Connected firms were more likely to form partnerships, namely have more than one owner with different surnames. Forming a partnership could introduce diverse expertise, thus creating more opportunities for innovation.[14] Although the number of partnerships in the data is small (only 690 firms) it is disproportionately concentrated among the Connected firms – 89% of the partnerships had at least one Connected owner.

Table 5 presents the results. Connected-owned firms were more likely to employ women (Column 1), but did not employ a statistically significantly larger proportion of women (Column 2). Connected-owned firms did operate more days per year (Column 3) and were significantly more likely to operate as a partnership (Column 4). Next, we again look at the decomposition of Connected into different groups. 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 7), which would have generated higher revenue per

[12] In the US North-East, women played a large role in industrialization in the 19-th century (Goldin and Sokoloff, 1982).

[13] Gregg and Matiashvili (2022) show that operating more days per year and thus not leaving capital idle was associated with more factory-like operation in the late Russian Empire. We only look at firms that are at least one year old when using the Working Days variable as an outcome.

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

worker. They were also more likely to form a partnership (Column 8), which would have offered more diversified expertise in management. German-owned firms exhibited similar, even stronger patterns. Finally, while the Other Connected-owned firms did not operate longer, they were most likely to employ women and have more women in their workforce and were more likely to form partnerships.[15]

[15] We remind the reader that in 109 mixed-connected ownership firms, we assigned ownership to "Other connected" firms, which might bias this coefficient up with regard to the German and Jewish coefficients.

Table 5: Connected firms and management practices

	Employs Women (1)	Proportion Women (2)	log Working Days in 1894 (3)	Partnership (4)	Employs Women (5)	Proportion Women (6)	log Working Days in 1894 (7)	Partnership (8)
Connected	0.014*	0.003	0.022**	0.041***				
	(0.008)	(0.003)	(0.010)	(0.004)				
German					0.015	0.007	0.036**	0.046***
					(0.011)	(0.005)	(0.015)	(0.008)
Jewish					0.011	0.000	0.025**	0.032***
					(0.009)	(0.003)	(0.011)	(0.004)
Other Connected					0.020**	0.007**	0.011	0.064***
					(0.010)	(0.004)	(0.012)	(0.008)
log Age	-0.001	-0.001	0.020***	-0.008***	-0.001	-0.001	0.020***	-0.008***
	(0.002)	(0.001)	(0.003)	(0.002)	(0.002)	(0.001)	(0.003)	(0.002)
log Num. Empl.	0.090***	0.020***	0.091***	0.013***	0.090***	0.020***	0.091***	0.013***
	(0.005)	(0.002)	(0.007)	(0.002)	(0.005)	(0.002)	(0.007)	(0.002)
Factory is located in a city	-0.005	-0.007	0.060***	0.019***	-0.005	-0.006	0.060***	0.020***
	(0.012)	(0.006)	(0.021)	(0.006)	(0.012)	(0.006)	(0.021)	(0.006)
N	15,687	15,687	15,414	15,687	15,687	15,687	15,414	15,687
Mean	0.242	0.075	5.254	0.043	0.242	0.075	5.254	0.043
R-squared	0.560	0.508	0.465	0.121	0.560	0.509	0.465	0.123
District FE	✓	✓	✓	✓	✓	✓	✓	✓
Indsutry + Main Activity FE	✓	✓	✓	✓	✓	✓	✓	✓

Notes: Outcome variables: in columns 1 & 5 is whether a firm employs women; in columns 2 & 6 is what proportion of the workforce is women; in columns 3 & 7 is the log number of days the firm was open; in columns 4 & 8 is whether a firm was a partnership.

4 Establishing 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 of this variation. We suggest that connected firms enjoyed lower transaction costs in adopting technical and organizational know-how from the West. However, testing this hypothesis is challenging since the 1894 Manufacturing Census does not contain data on firms' foreign trade operations or any other information on direct contacts with foreign companies. Hence, we present several different results using the combination of the Manufacturing and novel sources to speak to establish this mechanism to the extent possible, by showing results confirming our proposed mechanism and exploring alternative ones.

4.1 1893 Chicago World's Fair

The Chicago World's Fair (also known as World's Columbian Exposition) was held in Chicago in October 1893, representing technological and cultural advancements of industrial nations in the late 19$^{\text{th}}$ century. The Russian Empire had 1,022 exhibits from eleven different exhibition groups. While most of the exhibits were inventions or individual art pieces, approximately a fifth were private firm exhibits demonstrating firms' products. The Russian Ministry of Finance published a catalog of all exhibits, including those of private firms, with blurbs describing each firm in detail – industry, founding year, output, revenue, etc. (Ministry of Finance, 1893). We use this catalog to explore the connections of Russian industrial firms to the West.

We are able to match 122 firms from the exhibition catalog with the 1894 Manufacturing Census. This sub-sample is heavily biased toward more productive and innovative firms since the Russian government selected participants to demonstrate the industrial progress of the Russian Empire. As shown in Table D6, firms that participated in the fair had 27% higher revenue per worker, 19% higher TFP, and 19% more machine power than their counterparts that were not selected for the fair (conditional on industry and more district fixed effects).

In the fair data, we observe whether firms (1) export their products abroad to any foreign country, (2) export their products to a European country, (3) import materials from any foreign country, and

(4) import materials from a European country. The data also include the founding year, number of workers and urban location indicator, similar to what we have in the manufacturing census. In addition, the fair firms show sufficient variation in the cultural origins of their owners. Hence, despite a highly selected sample, we can perform a similar regression analysis as before, but with import and export variables on the left-hand side. This allows us to test whether connected firms had direct links to Europe enabling knowledge exchange.

Table 6 presents these results. Panel A shows the full sample of firms at the fair. Columns (1) and (2) present suggestive evidence that Germans and 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 both import and export with Europe. The same patterns hold in Panel B, where we only look at the sample of firms that matched with the 1894 Census, although the statistical power is lower due to a smaller sample.

Table 6: Foreign trade: evidence from 1893 Chicago World's Fair

	Abroad		To Europe	
	(1) Import	(2) Export	(3) Import	(4) Export
	Panel A: Full Sample			
German	0.062	0.180	0.106*	0.315**
	(0.051)	(0.161)	(0.044)	(0.119)
Jewish	0.019	0.007	0.016	0.039
	(0.059)	(0.101)	(0.087)	(0.033)
Other Connected	0.148***	0.161	0.126***	0.153
	(0.037)	(0.205)	(0.018)	(0.133)
N	227	249	191	207
Mean Y_0	0.331	0.279	0.106	0.062
R-squared	0.251	0.139	0.120	0.167
Industry FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
	Panel B: Matched Sample			
German	-0.125	0.141	-0.042	0.338**
	(0.095)	(0.125)	(0.099)	(0.120)
Jewish	0.011	0.011	0.076	0.068
	(0.051)	(0.133)	(0.062)	(0.035)
Other Connected	0.247*	0.207	0.202	0.210*
	(0.104)	(0.275)	(0.101)	(0.092)
N	107	114	89	92
Mean Y_0	0.364	0.333	0.116	0.043
R-squared	0.249	0.120	0.127	0.245
Industry FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓

Notes: Robust standard errors clustered at the Industry Section 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 export (column 3) is limited to firms that specify what countries they are importing from. The same logic applies to exports in column (4)

The results suggest that, even among the most successful firms in the Russian Empire, there were differences in their trade behavior that 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 technological adoption and know-how exchange with advanced nations. While these data do not enable us to observe which technologies were imported from the West, they do confirm that such transfers would have been possible, given their close trade ties.

4.2 German owners and Germany's comparative advantage

If it is indeed the case that the Connected firms' productivity premium originated from their superior industrial knowledge, then the premium should be most pronounced in industries where the origin country had a comparative advantage at the time. Of foreigners, we are best able to identify German entrepreneurs. Hence, in this subsection, we identify the most advanced industries in Germany in the late 19^{th} century (as established in the economic and business history literature). Then we estimate the productivity premium of German firms in Russia separately for each industry, and see if we observe any matches between the two sets of industries.

According to Hungerland and Wolf (2022), Germany went through the Second Industrial Revolution "with industrial growth especially in machinery, chemicals, and electro-technical goods". Germany's increasing industrial might in heavy machinery and chemicals came to rival Britain as Europe's primary industrial nation in the decades preceding WWI (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).

Based on these accounts and given our industry classification, we should expect that German entrepreneurs in Russia enjoyed higher productivity in such industries as Metals and Machines, Chemicals, 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. Indeed, we find a large and statistically significant productivity premium in Chemicals – German-owned firms in this industry had, on average, 81% higher revenue per worker than Russian-owned firms.

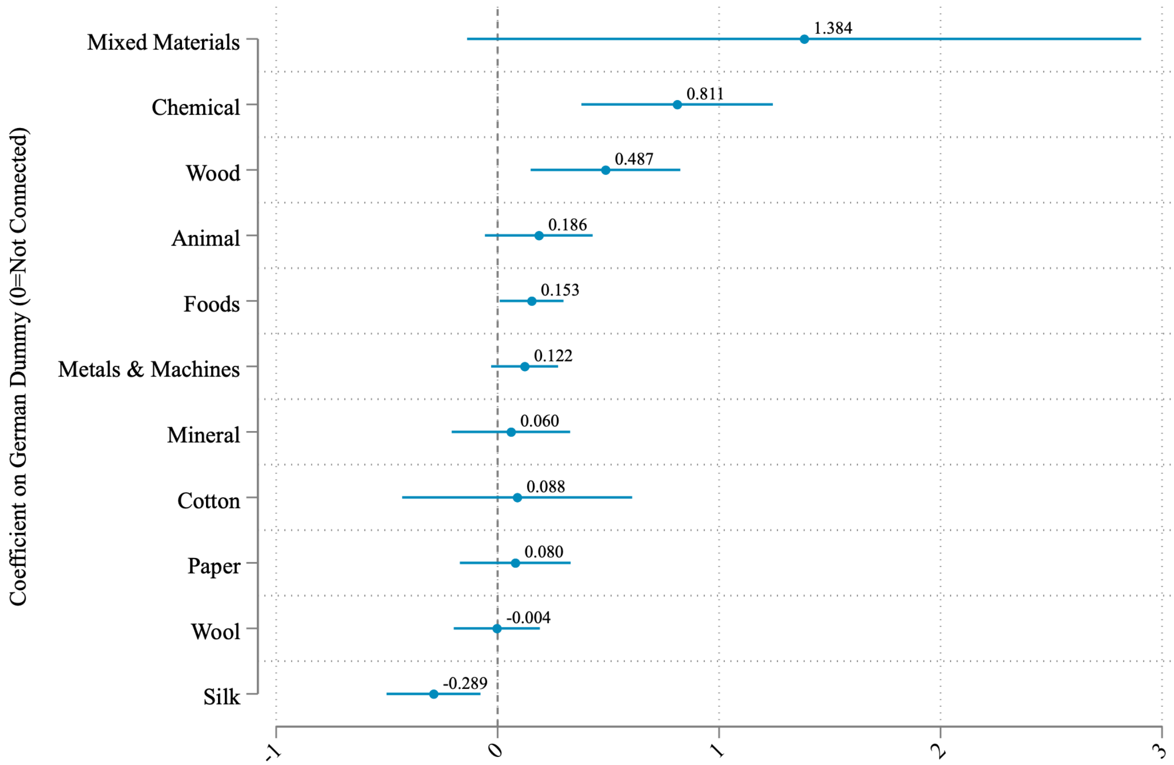


Figure 2: German productivity premium by industry (log Revenue per Worker)

Notes: The outcome variable in all specifications is log revenue per worker. Industries represented as they defined in the 1894 Manufacturing Census. The coefficients on German dummy show the average difference in log revenue per worker between German-owned firms and non-Connected firms (Russian and Eastern minorities) conditional on firm age, number of employees, urban location, and district fixed effects. Bars represent 95% confidence interval.

We also observe a positive and 10% statistically significant coefficient for Metals and Machines, which is consistent with the proposed mechanism. Similarly, we observe a large coefficient on Mixed Materials - as described below, this is due to the non-connected firms' overall disadvantage in this industry. Positive but insignificant coefficients for Wood, Animal products and Food processing imply that German firms in these industries probably benefited from imported machinery allowing them to process raw materials more efficiently. However, other factors, such as quality of local inputs, might counterbalance the machine advantage. Interestingly, the estimated coefficients for textiles (especially cotton and wool) and mining are zero. Hence, we do not observe any "German premium" for industries in which Germany had no comparative advantage at the time.

It is, however, possible that the German advantage in Chemicals is coming entirely from Russian inferiority in it. In Table E8, we look at the same decomposition, but looking at all Connected groups *except for* Germans. The coefficient for the Chemicals industry is now zero, suggesting that, indeed, this difference was due to the German factor specifically. By contrast, the coefficient on mixed materials remains large and, in this case, statistically significant, pointing to a true disadvantage of the non-connected firms in this industry.

To complete the story, we present examples of the German-classified entrepreneurs in the chemicals industry, showing that they indeed had direct connections to Germany and Europe, which would have enabled knowledge transmission and, thus, productivity boost.

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 [16]. 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 suspense [17]. 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

[16] source: `https://www.dp.ru/a/2019/08/29/Fabrichnij_aromat`

[17] `http://www.raruss.ru/excellent/2737-leman-gravure.html`

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.

4.3 Local spillover effects

In the previous subsections, we presented indirect evidence of technology diffusion from abroad. However, a significant share of innovation spillovers happens locally when less productive firms try to emulate a domestic "role model" in their industry. We then ask, did non-Connected firms with higher exposure to Connected firms operating in the same market 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 a district-industry pair's labor employed by connected firms, normalized by all labor in the district-industry pair. We then include this variable in the regression equation to compare the productivity measures of a non-connected firm in a given district and industry-primary activity pair to other non-connected firms in a different district but the same province industry-primary activity pair. Hence, we estimate the following equation:

$$Y_{i,d,j} = \beta \text{SEC}_{idj} + \delta X_{idj} + \theta_j + \psi_p + \varepsilon_{idj}, \tag{2}$$

where SEC_{idj} is the share of Connected firms' employees in total employment in district d in industry i, or more formally

$$SEC_{idj} = \frac{\text{\# employees of "Connected" firms}_{idj}}{\text{total number of all firms' employees}_{idj}}.$$

Figure 3 presents the results of this estimation. Indeed, firms surrounded by more Connected firms exhibited higher productivity measured by TFP and a higher likelihood of using machines[18]. Interestingly, the increase in TFP seems to be driven by the likelihood of using engines. The non-connected firms seem not to have adopted any of the beneficial management practices. Extrapolating from the findings by Giorcelli (2019), these non-connected firms may not have enjoyed productivity boosts for long, as management practice innovations would be necessary for long-term

[18] The coefficients found here are an order of magnitude larger than that in our baseline results - this is due to the measure that we are using. In our baseline analysis, the coefficients capture the binary effect of connected versus non-connected firms. Here, the continuous measure captures the effect of going from no to all manufacturing labor employed by connected firms in one's province and industry-primary activity pair.

success.

However, at least in the short term, these results present evidence of knowledge spillovers at the local level between more advanced firms with cultural connections to the West and firms without such connections.

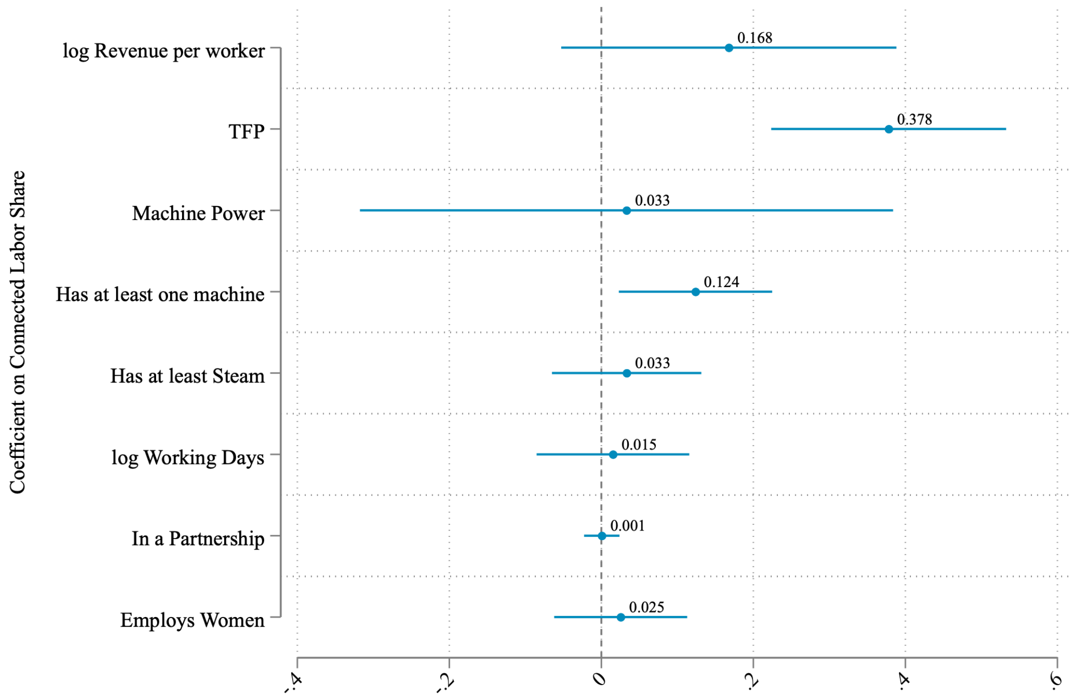


Figure 3: Spillovers from Connected to Non-connected firms

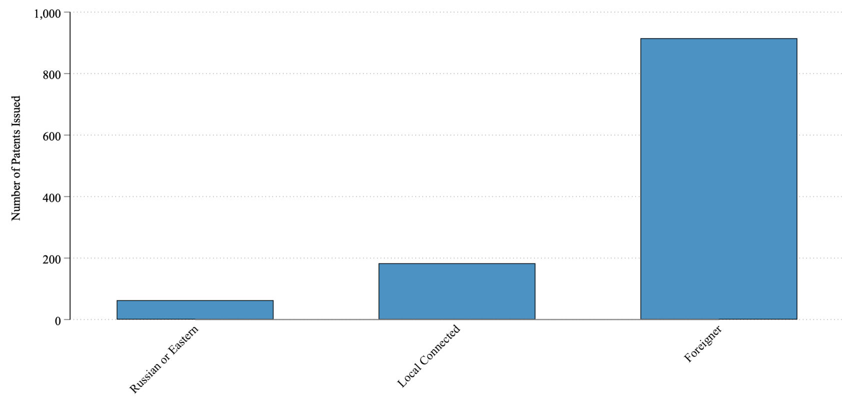
Notes: The coefficients on the share of Connected firms show the average differences in productivity measures between non-Connected firms with different exposure to Connected firms conditional on firm age, number of employees, urban location, and industry-primary activity fixed effects. Bars represent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

4.4 Patents

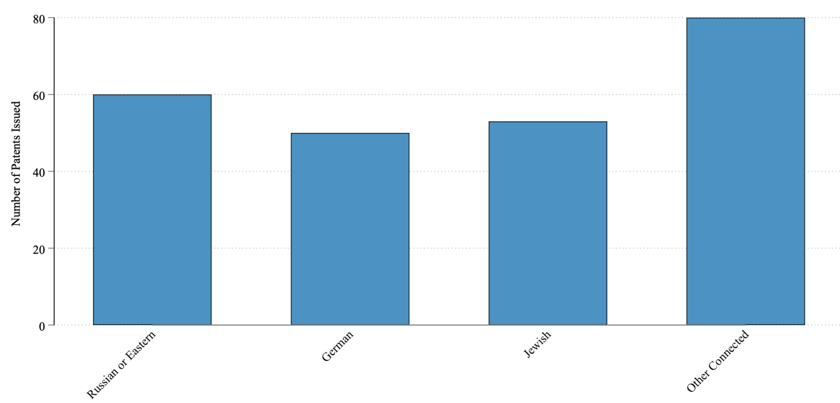
Patenting is often used as a proxy for innovative activity. While the main focus of our study is innovation diffusion, it can beget further innovation. We digitized the universe of patents issued in the Russian Empire in 1892-1896. There were a total of 1,161 patents issued to individuals over this period.[19] Most of them, 915, were issued to foreign nationals (see Figure 4a), part of

[19]We drop patents issued to corporations.

it due to cross-patenting from other nations. This in itself is a very telling fact.[20] 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). 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%.



(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

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. Jewish last names were identified using Beider (2008)'s dictionary of Jewish last names in the Russian Empire.

[20]Many patents assigned to foreign nationals may stem from international patenting, where the inventor resided in a different country but applied for a patent in many countries, as is common today.

4.5 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 F9 presents these results. While negative, as expected, the effect of distance was small and statistically insignificant.

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.

Were connected firms more likely to enjoy the benefits of cities compared to the non-connected firms? It is well-known that locational choices have a big effect on outcomes – for instance, Abramitzky et al. (2020) find that the upward mobility of immigrants' children in the United States is largely driven by the immigrants choosing wealthier locations as their destinations. 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 would provide easier connection to and trade with other countries. While we cannot directly test the latter part of the argument, we can see whether connected entrepreneurs benefitted more from locating in cities, providing at least suggestive evidence.

We identify seventeen cities from the 1897 Russian Empire Population Census with a population greater than one hundred thousand. These were the largest cities of the Empire. 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 found in 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 large and significant for all outcomes (Columns 1 - 3 of Table 7). The interaction was positive for all ethnicities, and statistically significant for the

Jewish and Other Connected groups (Columns 4-6 of Table 7). 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.

Table 7: Connected Entrepreneurs and Location Choices

	log Revenue per worker (1)	TFP (2)	Machine Power (3)	log Revenue per worker (4)	TFP (5)	Machine Power (6)
Connected × City >100k pop.	0.127***	0.097***	0.237**			
	(0.039)	(0.037)	(0.095)			
German × City >100k pop.				0.135*	0.093	0.120
				(0.069)	(0.067)	(0.186)
Jewish × City >100k pop.				0.117**	0.087*	0.254***
				(0.046)	(0.047)	(0.096)
Other Connected × City >100k pop.				0.151***	0.124***	0.277
				(0.044)	(0.039)	(0.177)
City >100k pop.	0.058	0.092	-0.171	-0.089	0.091	-0.161
	(0.079)	(0.065)	(0.129)	(0.091)	(0.065)	(0.130)
Connected	0.064***	0.057**	0.034			
	(0.024)	(0.024)	(0.040)			
German				0.096***	0.064*	0.086
				(0.036)	(0.036)	(0.069)
Jewish				0.064**	0.068***	0.007
				(0.026)	(0.026)	(0.044)
Other Connected				0.036	0.023	0.067
				(0.029)	(0.029)	(0.048)
N	13,451	13,451	14,808	13,451	13,451	14,808
Mean	6.851	-0.016	21.253	6.851	-0.016	21.253
R-squared	0.490	0.443		0.492	0.443	
District FE	✓	✓	✓	✓	✓	✓
Indsutry + Main Activity 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.

5 Eliminating alternative mechanisms

To isolate the knowledge transmission mechanism, we must rule out salient competing explanations. In this section, we present evidence that 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 and access to output markets, do not explain the "connected" firms' productivity premium.

5.1 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 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. 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, employing equal number of workers in the same industry and same 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 8: Sub-sample of firms without machines

	log Revenue per worker (1)	TFP (2)	log Revenue per worker (3)	TFP (4)
Connected	0.088***	0.088***		
	(0.031)	(0.031)		
German			0.157**	0.157**
			(0.062)	(0.062)
Jewish			0.078**	0.078**
			(0.032)	(0.032)
Other Connected			0.102***	0.102***
			(0.038)	(0.038)
log Age	0.060***	0.060***	0.060***	0.060***
	(0.010)	(0.010)	(0.010)	(0.010)
log Num. Empl.	-0.059*	0.066**	-0.059*	0.066**
	(0.030)	(0.030)	(0.030)	(0.030)
Factory is located in a city	0.132**	0.132**	0.133***	0.133***
	(0.052)	(0.052)	(0.052)	(0.052)
N	5,350	5,350	5,350	5,350
Mean	6.580	0.026	6.580	0.026
R-squared	0.576	0.575	0.576	0.575
District FE	✓	✓	✓	✓
Indsutry + Main Activity FE	✓	✓	✓	✓

SEs clustered at District level. The outcome variable of:

Columns 1 & 3 log revenue per worker. Columns 2 & 4 is residual TFP.

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

Table 8 presents the results. The coefficient on log revenue per worker and TFP are roughly of the same magnitude as those in Table 3. Of course, given no machine power in these firms, the TFP and log revenue per worker measures here are equivalent. The pattern of the coefficients is also similar to the whole sample estimation for the German and Jewish firms. The coefficient for the "other connected" group is almost twice as large, suggesting that this group's overall productivity advantage may largely stem management rather than the capital margin, which we also observed in Table 5.

5.2 Education

Another concern with our interpretation of the results is that we may be capturing the effect of a different type of human capital - education. 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 very high literacy rates ($\geq$ 75%, 6% of the sample) as captured by the 1897 Population Census. While literacy is only an imperfect proxy for education, such high literacy is likely associated with high education levels of population. Table 9 shows that even within such a small and positively selected sample, productivity premia for the connected firms hold and are even larger than the baseline results.

5.3 In-group bias

Another 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 Russian 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% 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 should introduce a downward bias

Table 9: Literacy and Productivity Measures, $\geq$ 75% literate

	log Revenue per worker (1)	TFP (2)	Machine Power (3)	log Revenue per worker (4)	TFP (5)	Machine Power (6)
Connected	0.342**	0.346**	0.119			
	(0.143)	(0.137)	(0.233)			
German				0.317**	0.336**	0.065
				(0.147)	(0.152)	(0.189)
Jewish				0.368**	0.372**	0.180
				(0.155)	(0.147)	(0.257)
Other Connected				0.299*	0.292**	-0.040
				(0.148)	(0.132)	(0.182)
log Age	0.061**	0.060**	0.000	0.062**	0.061**	-0.004
	(0.023)	(0.027)	(0.031)	(0.024)	(0.028)	(0.030)
log Num. Empl.	0.088	0.076	0.909***	0.092	0.079	0.903***
	(0.064)	(0.060)	(0.130)	(0.063)	(0.059)	(0.131)
Factory is located in a city	0.458***	0.415**	0.400***	0.453***	0.414**	0.406***
	(0.147)	(0.152)	(0.154)	(0.148)	(0.154)	(0.129)
Noble last name	-0.043	-0.045	0.017	-0.059	-0.055	-0.026
	(0.097)	(0.088)	(0.129)	(0.095)	(0.090)	(0.112)
Observations	757	757	862	757	757	862
Mean Depent Variable	7.215	0.198	13.629	7.215	0.198	13.629
R-squared	0.611	0.575		0.611	0.576	
District FE	✓	✓	✓	✓	✓	✓
Industry + Main Activity FE	✓	✓	✓	✓	✓	✓

in our estimates on Connected firms dummy. Instead, the results are almost identical to Table 3, suggesting that they are not driven by in-group bias in non-Russian districts.

5.4 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 output markets through ethnic networks, both locally and through diasporas in other provinces. Mejia (2018), for instance, finds that social networks mattered greatly during the industrialization in Colombia in the late 19$^{\text{th}}$-early 20$^{\text{th}}$ centuries. In our setting, we know that strong spatial networks existed in Jewish communities.[21] Our data, however, does not allow us to reconstruct networks of firms and entrepreneurs.

The network effect could also enhance knowledge diffusion – individuals of the same ethnicity may

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

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

	log Revenue per worker (1)	TFP (2)	Machine Power (3)	log Revenue per worker (4)	TFP (5)	Machine Power (6)
Connected	0.082***	0.073***	0.068			
	(0.023)	(0.022)	(0.044)			
German				0.096**	0.056	0.051
				(0.038)	(0.036)	(0.099)
Jewish				0.081***	0.077***	0.048
				(0.025)	(0.024)	(0.048)
Other Connected				0.079***	0.065**	0.116
				(0.027)	(0.026)	(0.076)
log Age	0.045***	0.046***	-0.010	0.045***	0.046***	-0.010
	(0.007)	(0.007)	(0.014)	(0.007)	(0.007)	(0.014)
log Num. Empl.	0.071***	0.045**	0.953***	0.071***	0.045**	0.952***
	(0.020)	(0.020)	(0.030)	(0.020)	(0.020)	(0.030)
Factory is located in a city	0.200***	0.207***	-0.045	0.200***	0.207***	-0.042
	(0.038)	(0.035)	(0.054)	(0.038)	(0.035)	(0.052)
noble	-0.021	-0.018	0.011	-0.020	-0.020	0.018
	(0.022)	(0.021)	(0.043)	(0.022)	(0.022)	(0.042)
Observations	11,858	11,858	12,768	11,858	11,858	12,768
Mean Depent Variable	6.820	-0.034	22.148	6.820	-0.034	22.148
R-squared	0.500	0.453		0.500	0.453	
District FE	✓	✓	✓	✓	✓	✓
Industry + Main Activity FE	✓	✓	✓	✓	✓	✓

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

transmit entrepreneurial know-how within local 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 hope is to exclude the networks mechanism to make sure our ethnic background dummies capture mostly knowledge diffusion from abroad. To this purpose, we estimate the following equation:

To this end, we repeat the analysis presented in equation (1) but add interaction with the number of firms in the same district and industry, but not the same primary activity, owned by the same ethnicity-names as the firm. This way, we capture a proxy for upstream-downstream firms owned by the same-ethnicity entrepreneurs in a given market.

Table 11 presents the results. Columns 1 and 3 present baseline results without industry fixed effects, while Columns 2 and 4 add industry 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.

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

	log Rev/Worker		TFP	
	(1)	(2)	(3)	(4)
Share same ethn.	0.054	0.224**	0.106	0.199**
	(0.114)	(0.093)	(0.105)	(0.088)
Jewish	0.309***	0.228***	0.268***	0.204***
	(0.075)	(0.064)	(0.069)	(0.061)
German	0.229***	0.253***	0.164**	0.179***
	(0.082)	(0.071)	(0.071)	(0.063)
Other Connected	0.217***	0.197***	0.193***	0.168***
	(0.073)	(0.067)	(0.066)	(0.062)
Share same ethn. $\times$ Jewish	-0.492***	-0.225*	-0.400***	-0.188
	(0.155)	(0.129)	(0.142)	(0.122)
Share same ethn. $\times$ German	-0.280	-0.195	-0.201	-0.116
	(0.204)	(0.148)	(0.190)	(0.143)
Share same ethn. $\times$ Other Connected	-0.387**	-0.238*	-0.386***	-0.225*
	(0.163)	(0.138)	(0.148)	(0.131)
N	13,592	13,592	13,592	13,592
Mean Y_0	6.660	6.660	-0.149	-0.149
R-squared	0.215	0.350	0.217	0.324
District FE	✓	✓	✓	✓
Industry FE		✓		✓
Firm Controls	✓	✓	✓	✓

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

6 Conclusion

We document substantial productivity gains for industrial firms with cultural connections to the technological frontier in the late 19th century Russian Empire. We show that these productivity gains stemmed from both the adoption of advanced machinery and superior management practices. We use additional data sources to show that connected firms were more likely to trade with Europe, applied to and received more patents, and exhibited higher productivity in the same industries as their European counterparts, i.e., the chemical industry for German-owned firms. In addition, we show that connected firms likely served as role models for local non-connected firms, inducing spillovers of machinery adoption.

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 19^{th}-early 20^{th} 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 three decades before World War I (Markevich and Nafziger, 2017), while in the Ottoman Empire industrialization remained limited and the adoption of the steam engine was mostly concentrated in transport (Pamuk, 2019). Although both empires were multi-ethnic, only in the Russian case several notable ethnic minorities had direct cultural connections with industrialized Western Europe. These groups played a decisive role in the adoption of modern technologies and management practices from the West. Hence, the presence of connected minorities in Russia compensated, to some extent, for the institutional deficiencies and allowed for relatively faster growth of private manufacturing firms. The Ottomans were spared of that advantage, and industrialization before 1914 was mostly confined to the government-sponsored construction of railways.

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 will be explored in the future.

References

Abramitzky, Ran, Leah Platt Boustan, and Dylan Connor, “Leaving the Enclave: Historical Evidence on Immigrant Mobility from the Industrial Removal Office,” *National Bureau of Economic Research*, June 2020.

_ , _ , **and Katherine Eriksson**, “A Nation of Immigrants: Assimilation and Economic Outcomes in the Age of Mass Migration,” *Journal of Political Economy*, 2014, *122* (3), 467–506. Publisher: The University of Chicago Press.

Artunç, Cihan and Timothy W Guinnane, "Partnership as Experimentation," *The Journal of Law, Economics, and Organization*, November 2019, *35* (3), 455–488.

Ashraf, Quamrul and Oded Galor, "Cultural Diversity, Geographical Isolation, and the Origin of the Wealth of Nations," *NBER Working Paper No. 17640*, 2011.

Beider, Alexander, *A Dictionary of Jewish Surnames from the Russian Empire*, Avotaynu, 2008.

Bloom, Nicholas, Aprajit Mahajan, David McKenzie, and John Roberts, "Do Management Interventions Last? Evidence from India," *American Economic Journal: Applied Economics*, April 2020, *12* (2), 198–219.

_ , Erik Brynjolfsson, Lucia Foster, Ron Jarmin, Megha Patnaik, Itay Saporta-Eksten, and John Van Reenen, "What Drives Differences in Management Practices?," *American Economic Review*, May 2019, *109* (5), 1648–1683.

Caselli, Francesco and Wilbur John Coleman, "Cross-Country Technology Diffusion: The Case of Computers," *American Economic Review*, 2001, *91* (2), 328–335.

Cinnirella, Francesco, Erik Hornung, and Julius Koschnick, "Flow of Ideas: Economic Societies and the Rise of Useful Knowledge," *CESifo Working Paper*, 2022.

Comin, Diego and Bart Hobijn, "An Exploration of Technology Diffusion," *American Economic Review*, 2010, *100* (5), 2031–2059.

_ and Martí Mestieri, "If Technology Has Arrived Everywhere, Why Has Income Diverged?," *American Economic Journal: Macroeconomics*, 2018, *10* (3), 137–178.

Department of Trade and Manufacturing, *Directory Chronological, by Subject and Alphabetical of Privileges issued in Russia from Jan 1, 1892 to July 1, 1896 (Ukazatel' Khronicheskogo, Predmetnogo i Alfavitnogo Vyddanykh v Rossii Privilegiy s 1 yanvarya 1892 g. po 1 iyulya 1896 g.)*, Saint Petersburg: Typography of V. Kirschbaum, 1897.

Foster, Andrew D. and Mark R. Rosenzweig, "Microeconomics of Technology Adoption," *Annual Review of Economics*, 2010, *2* (1), 395–424.

Fouka, Vasiliki, "Backlash: The Unintended Effects of Language Prohibition in U.S. Schools after World War I," *The Review of Economic Studies*, January 2020, *87* (1), 204–239.

Fryer, Roland G. and Steven D. Levitt, "The Causes and Consequences of Distinctively Black Names," *The Quarterly Journal of Economics*, 2004, *119* (3), 767–805. Publisher: Oxford University Press.

Giorcelli, Michela, "The Long-Term Effects of Management and Technology Transfers," *American Economic Review*, January 2019, *109* (1), 121–152.

Goldin, Claudia and Kenneth Sokoloff, "Women, Children, and Industrialization in the Early Republic: Evidence from the Manufacturing Censuses," *The Journal of Economic History*, 1982, *42* (4), 741–774. Publisher: Cambridge University Press.

Gregg, Amanda, "Factory Productivity and the Concession System of Incorporation in Late Imperial Russia, 1894–1908," *American Economic Review*, 2020, *110* (2), 401–427.

— **and Steven Nafziger**, "Capital Structure and Corporate Performance in late Imperial Russia," *European Review of Economic History*, 2019, *23* (4), 446–481.

— **and** — , "The Births, Lives and Deaths of Corporations in Late Imperial Russia," *The Economic Journal*, 2024, *forthcoming*.

— **and Tamar Matiashvili**, "Modernization in Progress: Part-Year Operation, Mechanization, and Labor Force Composition in Late Imperial Russia," *The Journal of Economic History*, 2022, *82* (4), 1143–1182.

Griliches, Zvi, "Hybrid Corn: An Exploration in the Economics of Technological Change," *Econometrica*, 1957, pp. 501–522.

Gusev, Igor, *(XX) [History of Riga (From founding to the beginning of the 20th century)]*, Riga: IK «ZORIKS», 2020.

Hornbeck, Richard, Shanon Hsu, Anders Humlum, and Martin Rotemberg, "Gaining Steam: Incumbent Lock-in and Entrant Leapfrogging," April 2024.

Hornung, Erik, "Immigration and the Diffusion of Technology: The Huguenot Diaspora in Prussia," *American Economic Review*, 2014, *104* (1), 84–122.

Hsieh, Chang-Tai and Peter J. Klenow, "The Life Cycle of Plants in India and Mexico," *The Quarterly Journal of Economics*, August 2014, *129* (3), 1035–1084.

_ **and Peter J Klenow**, "The Life Cycle of Plants in India and Mexico," *The Quarterly Journal of Economics*, 2014, *129* (3), 1035–1084.

Hungerland, Wolf-Fabian and Nikolaus Wolf, "The panopticon of Germany's foreign trade, 1880–1913: New facts on the first globalization," *European Review of Economic History*, November 2022, *26* (4), 479–507.

Keller, Wolfgang, "International Technology Diffusion," *Journal of Economic Literature*, September 2004, *42* (3), 752–782.

Kindleberger, Charles P., "Germany's Overtaking of England, 1806 – 1914 Part II," *Weltwirtschaftliches Archiv*, 1975, *111* (3), 477–504. Publisher: Springer.

Lamoreaux, Naomi R., "Constructing Firms: Partnerships and Alternative Contractual Arrangements in Early Nineteenth-Century American Business," *Business and Economic History*, 1995, *24* (2), 43–71. Publisher: Cambridge University Press.

_ **and Jean-Laurent Rosenthal**, "Legal Regime and Contractual Flexibility: A Comparison of Business's Organizational Choices in France and the United States during the Era of Industrialization," *American Law and Economics Review*, March 2005, *7* (1), 28–61.

Manuelli, Rodolfo E. and Ananth Seshadri, "Frictionless Technology Diffusion: The Case of Tractors," *American Economic Review*, April 2014, *104* (4), 1368–91.

Markevich, Andrei and Steven Nafziger, "State and Market in Russian Industrialization, 1870–2010," in Kevin O'Rourke and Jeffrey Williamson, eds., *The Spread of Modern Industry to the Periphery Since 1871*, 2017, pp. 33–62.

Mejia, Javier, "Social Networks and Entrepreneurship: Evidence from a Historical Episode of Industrialization," June 2018.

Ministry of Finance, *World's Columbian Exposition 1893, Chicago. Catalogue of the Russian Section.*, Imperial Russian Commission, Ministry of Finance, 1893.

— , *Russian Factory Production: List of Factories and Plants. (Fabrichno-zavodskaya promyshlennost' Rossii: Perechen' fabrik i zavodov)*, Tipografia E.A. Efrona, 1897.

Mokyr, Joel, *The Lever of Riches: Technological Creativity and Economic Progress*, Oxford University Press, 1990.

— , "The Benefits and Costs of Diversity: Lessons from Economic History," in "Can Democracy and Capitalism Be Reconciled," Oxford University Press, forthcoming.

Pamuk, Şevket, "Uneven Centuries: Turkey's Experience with Economic Development since 1820," *The Economic History Review*, 2019, *72* (4), 1129–1151.

Russian Noble Assembly, *[General Armorial of the Noble Families of the Russian Empire]*, St. Petersburg: Miscellaneous, 1917.

Serafinelli, Michel and Guido Tabellini, "Creativity over Time and Space: A Historical Analysis of European cities," *Journal of Economic Growth*, 2022, *27* (1), 1–43.

Spitzer, Yannay, "Pogroms, Networks, and Migration: The Jewish Migration from the Russian Empire to the United States 1881–1914 *," *Maurice Falk Institute for Economic Research in Israel. Discussion paper series.*, 2021, (3), 0_1,1–41,43–83. Num Pages: 0_1,1-41,43-83 Place: Jerusalem, Israel Publisher: Maurice Falk Institute for Economic Research in Israel.

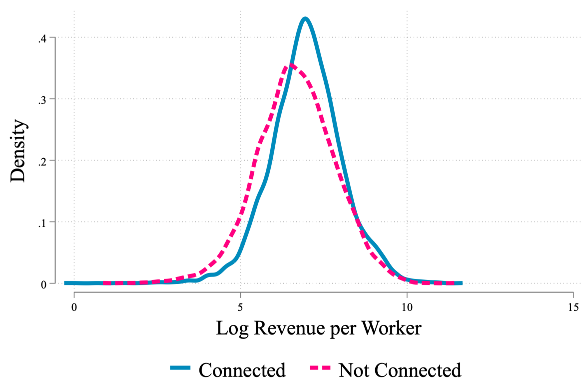
Spolaore, Enrico and Romain Wacziarg, "The Diffusion of Development," *The Quarterly Journal of Economics*, 2009, *124* (2), 469–529.

— **and** — , "Long-term Barriers to Economic Development," in Philippe Aghion and Steven N. Durlauf, eds., *Handbook of Economic Growth*, Vol. 2, Elsevier, 2014, pp. 121–176.

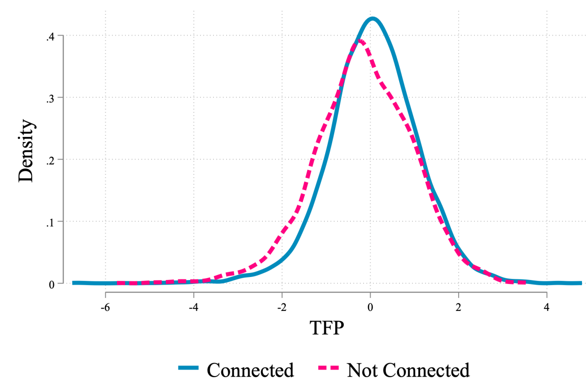
Squicciarini, Mara P and Nico Voigtländer, "Human Capital and Industrialization: Evidence from the Age of Enlightenment," *The Quarterly Journal of Economics*, 2015, *130* (4), 1825–1883.

Syverson, Chad, "What Determines Productivity?," *Journal of Economic literature*, 2011, *49* (2), 326–365.

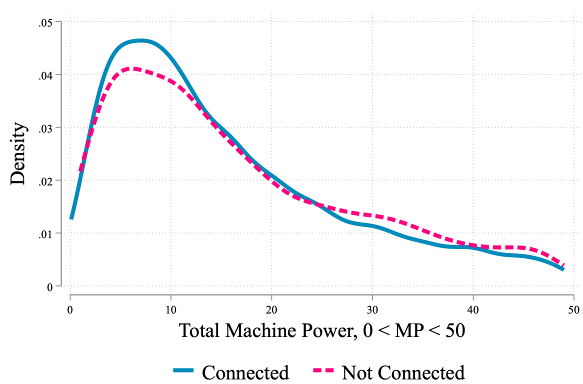
A Descriptive Statistics



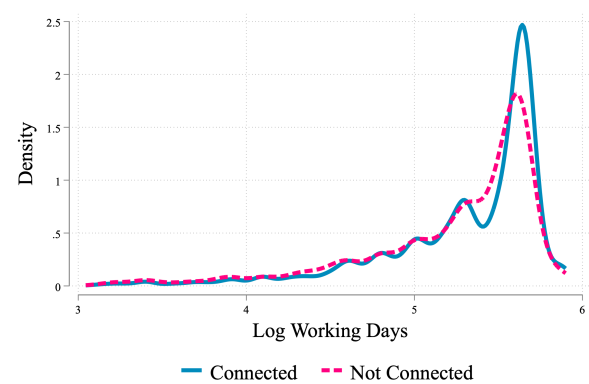
(a) Log Revenue Per Worker



(b) TFP



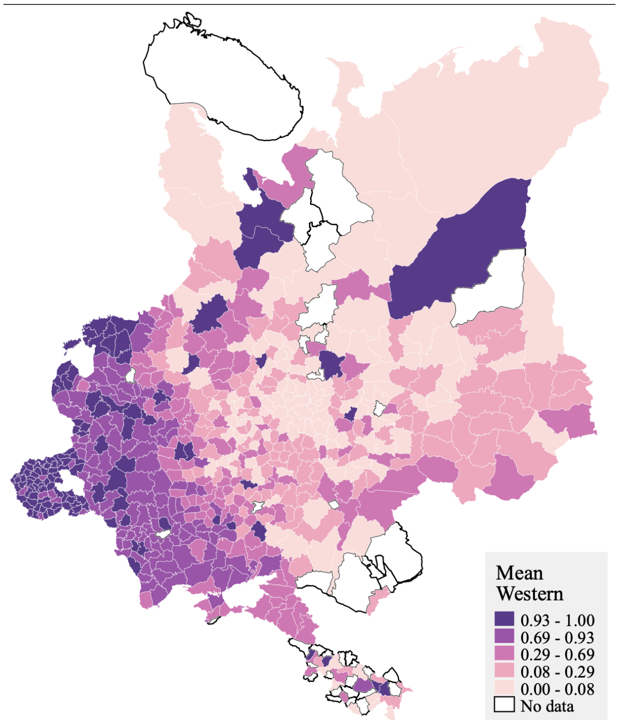
(c) Log Machine Power Per Worker



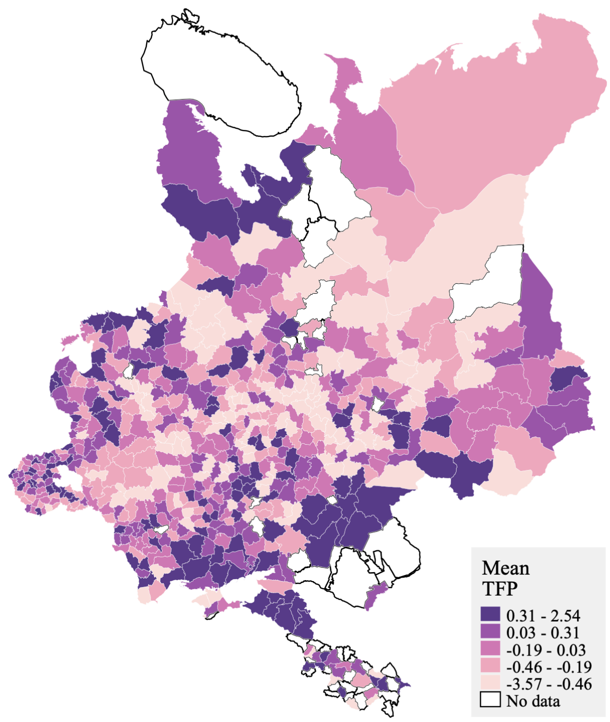
(d) Log Working Days

Figure A1: Density of select outcomes by group

Kernel densities of all variables are shifted to the right in the case of the Connected group, compared to the Non-Connected group.



(a) Share Connected firms



(b) Mean TFP

Figure A2: Spatial Distribution of Connected Firms and TFP

While “Connectedness" and TFP do not exhibit perfect spatial correlation, some spatial patterns are still evident in the map.

B Larger Firms

The inclusion criterion for this census was rather loose: a factory was included in the 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 B1: Connected Productivity Measures, $\geq$ 15 employees

	log Revenue per worker (1)	TFP (2)	Machine Power (3)
Connected	0.084***	0.066***	0.106**
	(0.023)	(0.023)	(0.050)
log Age	0.046***	0.046***	-0.004
	(0.007)	(0.008)	(0.018)
log Num. Empl.	0.039**	-0.043**	0.990***
	(0.016)	(0.018)	(0.040)
Factory is located in a city	0.120***	0.145***	-0.031
	(0.033)	(0.030)	(0.053)
N	6,974	6,974	7,094
Mean	6.828	0.002	35.679
R-squared	0.606	0.541	
District FE	✓	✓	✓
Indsutry + Main Activity FE	✓	✓	✓

C Jewish Entrepreneurs

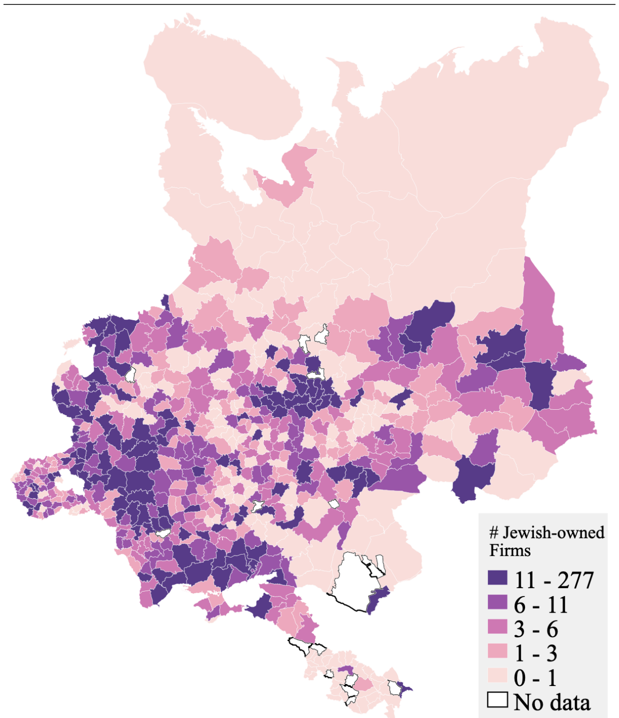
C.1 Jews in the Pale

We explore the spatial distribution of Jewish owners with respect to the pale of settlement. As discussed in the Historical Background section, 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.

In Table C2 we show that Jews inside and outside of the Pale (here defined as the official Pale + the Congress Poland Provinces described in the Historical Background) ran very different factories indeed. Considering factories in the same activities, Jews in the pale seemed to have fewer employees and more capital, were more likely to have capital, and had higher log revenue per worker compared to the outside-of-the-pale Jews. This suggests that Jews in the pale benefited from the network effects or less discrimination from outsiders from living in the pale.

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 Jew and was located within the Pale of settlement. In column the outcome variable is the log of revenue divided by the number of workers. In column 2, it is the residualized TFP, obtained by regressing log revenue per worker(+1) on log number of workers(+1) and log total machine power(+1).

(a) Pale of Settlement



(b) # factories owned by Jews

Figure C3: Pale of Settlement and Jewish Factories

Table C2: Pale vs Non-Pale Jews

	log Revenue per worker (1)	TFP (2)	Machine Power (3)
Jews in Pale	0.093***	0.080***	-0.156***
	(0.029)	(0.029)	(0.051)
log Age	0.032***	0.030***	-0.010
	(0.010)	(0.010)	(0.025)
Num. empl.	0.109***	0.090***	0.878***
	(0.014)	(0.013)	(0.030)
City_dummy	0.325***	0.308***	0.268***
	(0.033)	(0.033)	(0.069)
N	4,635	4,635	5,010
R-squared	0.415	0.362	
Industry + Main Activity FE	✓	✓	✓

C.2 Robustness to excluding Jewish owners

Jewish entrepreneurs were crucial in the economy of the Russian Empire. They operated 5,654 (34.7%) 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 ans 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 C3: Connected Ownership and Productivity Measures, excluding Jewish-classified owners

	log Revenue per worker (1)	TFP (2)	Machine Power (3)	log Revenue per worker (4)	TFP (5)	Machine Power (6)
Connected	0.105***	0.078***	0.117*			
	(0.031)	(0.028)	(0.061)			
German				0.151***	0.109***	0.096
				(0.036)	(0.033)	(0.109)
Jewish						
Other Connected				0.086***	0.064**	0.126*
				(0.031)	(0.029)	(0.069)
log Age	0.044***	0.045***	-0.008	0.044***	0.045***	-0.008
	(0.008)	(0.008)	(0.017)	(0.008)	(0.008)	(0.017)
log Num. Empl.	0.083***	0.056***	0.953***	0.083***	0.056***	0.952***
	(0.021)	(0.021)	(0.032)	(0.021)	(0.021)	(0.032)
Factory is located in a city	0.191***	0.208***	-0.040	0.192***	0.209***	-0.041
	(0.043)	(0.041)	(0.054)	(0.043)	(0.041)	(0.055)
Noble last name	-0.012	-0.017	-0.012	-0.011	-0.017	-0.012
	(0.029)	(0.028)	(0.057)	(0.029)	(0.028)	(0.057)
Observations	8,725	8,725	9,489	8,725	8,725	9,489
Mean Depent Variable	6.820	-0.051	21.893	6.820	-0.051	21.893
R-squared	0.500	0.459		0.500	0.459	
District FE	✓	✓	✓	✓	✓	✓
Industry + Main Activity FE	✓	✓	✓	✓	✓	✓

C.3 Russian and Non-Russian Jews

It is possible that only non-Russian Jews enjoyed the benefits of “connectedness” as they would be more likely to have connections to Jewish diasporas in Western Europe. We separate our sample by Russian-sounding (Russian last name endings) vs non-Russian sounding Jews. We indeed find that the entirety of the Jewish premium stems from the non-Russian Jews, strengthening our argument.

Table C4: Non-Russian versus Russian Jews

	(1) log Revenue per worker	(2) TFP	(3) Machine Power
German	0.135***	0.092***	0.108
	(0.037)	(0.033)	(0.090)
Non-Russian Jewish	0.110***	0.092***	0.087
	(0.037)	(0.034)	(0.070)
Russian Jewish	-0.041	-0.023	-0.065
	(0.040)	(0.038)	(0.081)
Other Connected	0.074**	0.052*	0.138**
	(0.031)	(0.028)	(0.069)
log Age	0.046***	0.046***	-0.004
	(0.007)	(0.007)	(0.013)
log Num. Empl.	0.068***	0.042**	0.931***
	(0.018)	(0.018)	(0.029)
Factory is located in a city	0.194***	0.196***	-0.032
	(0.034)	(0.032)	(0.047)
Noble last name	-0.016	-0.018	0.036
	(0.020)	(0.020)	(0.042)
Observations	13,451	13,451	14,806
Mean Depent Variable	6.851	-0.016	21.254
R-squared	0.492	0.446	
District FE	✓	✓	✓
Industry + Main Activity FE	✓	✓	✓

Notes: Robust standard errors clustered on the District level. Russian Jewish group defined as the last names we previously classified as Jewish, that end on Russian last-name endings such as "-ov", "-ev", and "-in".

C.4 Jewish Name Index by Abramitzky et al. (2020)

Abramitzky et al. (2020) crate 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 9,634 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 1-4). In addition, all the coefficients on German are also positive and significant (marginally, for TFP) (Columns 5-8). The coefficients on Jewish remain large and significant. Further, the coefficients on German and Other Connected remain similar as well. These results reassure us that our exact classification of Jewish last names does not alter the takeaways of our findings, and validates using the Dictionary of Jewish Last Names as our main source.

Table C5: Jewish Name Index: Connected Ownership and Productivity Measures

	log Revenue per worker (1)	TFP (2)	Machine Power (3)	log Revenue per worker (4)	TFP (5)	Machine Power (6)
Connected	0.063***	0.050**	0.092**			
	(0.022)	(0.022)	(0.046)			
German				0.103***	0.075**	0.078
				(0.033)	(0.033)	(0.077)
Jewish				0.000	0.000	0.000
				(.)	(.)	(.)
Other Connected				0.046**	0.035	0.097*
				(0.022)	(0.023)	(0.052)
log Age	0.046***	0.047***	-0.003	0.046***	0.046***	-0.003
	(0.007)	(0.007)	(0.013)	(0.007)	(0.007)	(0.013)
Num. empl.	0.067***	0.041**	0.931***	0.069***	0.042**	0.933***
	(0.018)	(0.018)	(0.030)	(0.018)	(0.019)	(0.030)
Factory is located in a city	0.199***	0.202***	-0.041	0.203***	0.205***	-0.034
	(0.035)	(0.032)	(0.048)	(0.035)	(0.033)	(0.051)
noble	-0.016	-0.013	0.025	-0.013	-0.011	0.029
	(0.020)	(0.020)	(0.042)	(0.020)	(0.020)	(0.041)
Observations	13,297	13,297	14,639	12,923	12,923	14,196
Mean Depent Variable	6.850	-0.016	21.182	6.842	-0.020	21.463
R-squared	0.493	0.446		0.496	0.450	
District FE	✓	✓	✓	✓	✓	✓
Industry + Main Activity FE	✓	✓	✓	✓	✓	✓

Notes: Robust standard errors clustered at District level. The outcome variable of: Columns 1 & 5 is log revenue per worker; Columns 2 & 6 is is residual TFP from a Cobb-Douglas production function of regressing log revenue(+1) on log total employment(+1) and log total machine power(+1); columns 3 & 7 is whether a factory has positive machine power that does not come from horses. Column 4 & 8 is hyperbolic sine of machine power.

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.

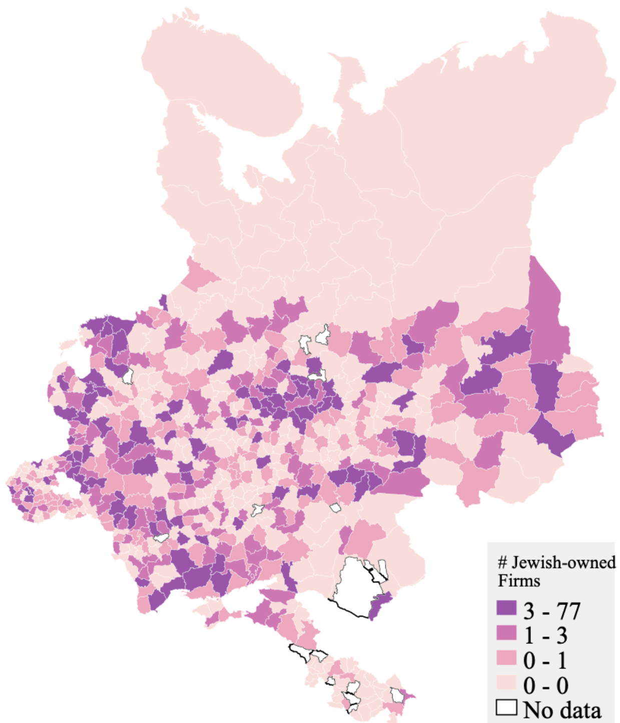


Figure C4: # factories owned by Jews, Jewish Name Index method

D Chicago World Fair

Table D6 shows that firms at the Chicago world 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 (1)	TFP (2)	Machine Power (3)
Participated in Fair	0.271***	0.193**	0.188*
	(0.079)	(0.078)	(0.103)
log Age	0.046***	0.046***	-0.007
	(0.006)	(0.006)	(0.012)
log avg. total num. of workers+1	0.064***	0.040***	0.935***
	(0.009)	(0.008)	(0.018)
Factory is located in a city	0.200***	0.202***	-0.049
	(0.023)	(0.023)	(0.040)
N	13,426	13,426	14,788
Mean Y_0	6.845	-0.022	20.731
R-squared	0.492	0.445	
District FE	✓	✓	✓
Indsutry + Main Activity FE	✓	✓	✓

SEs clustered at District level.

E Mechanism Robustness Checks

E.1 German advantage by Industry

Table E7: German productivity premium by Industry

	Log Revenue Per Worker											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Animal	Chemical	Cotton	Flax	Foods	Metals & Machines	Mineral	Mixed Materials	Paper	Silk	Wood	Wool
german$_{n}ot_{w}estern$	0.186	0.811***	0.088	0.000	0.153**	0.122	0.060	1.384*	0.080	-0.289**	0.487***	-0.004
	(0.123)	(0.214)	(0.254)	(.)	(0.073)	(0.076)	(0.135)	(0.736)	(0.123)	(0.094)	(0.169)	(0.096)
N	826	203	191	133	2,177	512	483	129	199	159	291	255
Mean	6.974	6.866	6.899	6.561	7.127	6.510	5.737	6.151	6.534	6.287	6.670	6.668
R-squared	0.611	0.805	0.491	0.495	0.530	0.560	0.611	0.847	0.489	0.445	0.657	0.598
District FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Main Activity FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

The outcome variable in all specifications is log revenue per worker. Each column represents one of 12 industries, specified by the 1894 Manufacturing Census.

E.2 Non-German advantage by Industry

Table E8: Non-German Connected Firms by Industry

	Log Revenue Per Worker											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Animal	Chemical	Cotton	Flax	Foods	Metals & Machines	Mineral	Mixed Materials	Paper	Silk	Wood	Wool
Western (not German)	0.043	-0.016	0.302	0.487	0.043	0.127	0.043	0.793***	0.066	-0.250*	0.189	0.294**
	(0.111)	(0.147)	(0.195)	(0.340)	(0.053)	(0.098)	(0.067)	(0.266)	(0.090)	(0.116)	(0.137)	(0.144)
N	861	220	198	140	2,853	507	551	144	253	161	336	252
Mean	6.981	6.812	6.897	6.592	7.056	6.511	5.740	6.154	6.495	6.280	6.747	6.683
R-squared	0.607	0.795	0.501	0.523	0.513	0.563	0.600	0.855	0.391	0.436	0.645	0.584
District FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Main Activity FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

F Distance

Table F9 interacts the distance of district centroids to the closest point on the European border with the Connected dummy.

Table F9: Complementarities of connectedness and distance to Europe

	(1) log Revenue per worker	(2) TFP	(3) Machine Power
Connected	0.102**	0.083**	0.139***
	(0.040)	(0.038)	(0.045)
Connected * Log Distance	-0.010	-0.006	-0.035
	(0.017)	(0.016)	(0.022)
log Age	0.045***	0.046***	-0.005
	(0.007)	(0.007)	(0.014)
log Num. Empl.	0.069***	0.043**	0.931***
	(0.017)	(0.018)	(0.030)
Factory is located in a city	0.194***	0.197***	-0.036
	(0.034)	(0.032)	(0.048)
Noble last name	-0.019	-0.016	0.021
	(0.019)	(0.019)	(0.042)
Observations	13,427	13,427	14,789
Mean Depent Variable	6.850	-0.017	21.223
R-squared	0.491	0.445	
District FE	✓	✓	✓
Industry + Main Activity FE	✓	✓	✓

Notes: Robust standard errors clustered on 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.