Return Innovation: The Knowledge Spillovers of the British Migration to the United States, 1870–1940*

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Abstract

This paper documents that out-migration promotes the diffusion of innovation from the country of destination to the country of origin of migrants. Between 1870 and 1940, nearly four million British immigrants settled in the United States. We construct a novel individual-level dataset linking British immigrants in the US to the UK census, and we digitize the universe of UK patents from 1853 to 1899. Using a triple-differences design, we show that migration ties contribute to technology diffusion from the destination to the origin country. The text analysis of patents reveals that emigration promotes technology transfer and fosters the production of high-impact innovation. Return migration is an important driver of this "return innovation" effect. However, the interactions between emigrants and their origin communities—families and neighbors—promote technology diffusion even in the absence of migrants' physical return.

Keywords: Age of Mass Migration, Innovation, Networks, Out-migration.

JEL Classification: F22, N73, N74, O15, O31, O33.

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I Introduction

The diffusion of new technologies across countries is a central driver of productivity growth and economic convergence (e.g., Eaton and Kortum, 1999; Griffith, Harrison and Van Reenen, 2006; Comin and Hobijn, 2010).[1] However, evidence on the mechanisms enabling technology to diffuse across countries is surprisingly scarce. In this paper, we provide novel evidence on the role of out-migration as a source of technology transfer from the country of destination to the country of origin of migrants. We label this phenomenon "return innovation."

The impact of emigration on innovation is *ex-ante* ambiguous. The traditional brain drain hypothesis argues that emigration countries suffer a loss of human capital (e.g., Docquier and Rapoport, 2012). Growth theory, in turn, predicts that this depletion would negatively affect their ability to innovate. On the other hand, recent evidence suggests that exposure to innovation is an important driver of technological change (Akcigit, Caicedo, Miguelez, Stantcheva and Sterzi, 2018; Bell, Chetty, Jaravel, Petkova and Van Reenen, 2019). We argue that, as migrants are exposed to innovation in the areas where they settle, they promote knowledge flows between those areas and their origin country, as documented qualitatively by Saxenian (2006).

We focus on the English and Welsh migration to the United States between 1850 and 1940.[2] During this period, also known as the "Age of Mass Migration," approximately 30 million European migrants settled across the Atlantic. Nearly four million came from England and Wales. Since Rosenberg (1982), economists have interpreted the spread of the Industrial Revolution in terms of waves of technological diffusion originating in Britain. Existing studies document that, as a result, European immigrants contributed to the diffusion of (mainly) British technology in the US (Jeremy, 1981). This pattern reflects the British technological leadership during the first half of the nineteenth century. Since as early as the 1860s, however, the US reached the technology frontier in many industries, from engines to agricultural machinery (David, 1966; Rosenberg, 1970).[3] In this paper, we document that migration

[1]Among others, Eaton and Kortum (1999) estimate that 70% of productivity growth in advanced European countries in the 1980s relied on technology developed in the United States and Japan. Several recent endogenous growth models include cross-country technology diffusion dynamics (e.g. Alvarez, Buera and Lucas, 2013; Buera and Oberfield, 2020; Perla, Tonetti and Waugh, 2021).

[2]Throughout the paper, we focus on England and Wales. With a slight abuse of language, we use the terms "Britain" and "United Kingdom" (UK) as shortcuts to collectively refer to England and Wales.

[3]By the 1890s, the American technological primacy was well-established. Nelson and Wright (1992) note that, starting in the 1880s, American technology saw major advancements in textiles, sewing machines, clocks, firearms, boots and shoes, locomotives, bicycles, and cigarettes. From the 1890s, mass production led to innovations in consumer products (canned goods, dairy, and grain products), light machinery (typewriters, cameras), electrical equipment, and industrial machinery, such as boilers, pumps, and printing presses.

networks promoted the diffusion of these technologies back to Britain.

We assemble two novel general-purpose datasets to overcome the limitations of the existing sources. First, since the available data do not contain information on the origin of British immigrants in the US beyond their country of origin, we use confidential individual-level UK and US census data to link the records of British immigrants in the US to the UK census (Schurer and Higgs, 2020; Ruggles, Fitch, Goeken, Hacker, Nelson, Roberts, Schouweiler and Sobek, 2021). This dataset enables us to track individual migration between the UK and the US, as well as return migration. Second, to reconstruct the geography of innovation in the UK in the second half of the nineteenth century, we digitize all 300,000 original patent documents issued in England and Wales between 1853 and 1899. This dataset allows us to cover the universe patents granted during the period of our analysis in the UK.

We build a measure of exposure to US innovation that is higher for districts with larger overseas emigrant communities and when the US counties that emigrants settle in are more innovative.[4] Our research design leverages the joint variation in county-level specialization across technology classes and district-county bilateral migration flows between UK districts and US counties.

Identifying the impact of exposure to US innovation on innovation in the UK presents several challenges. The primary reason that would caution against a causal interpretation of the estimates is assortative matching. Namely, British migrants could sort across US counties in a way that is correlated with innovation in their district of origin and in their county of destination. We develop two approaches to deal with this challenge. Our main identification strategy leverages episodes of unusually high patenting activity in the United States—which we label as "innovation shocks"— as shocks to exposure to US innovation. We examine how such shocks diffuse to the UK through emigration ties in double and triple differences designs. In a complementary approach, we build two instrumental variables. Specifically, we exploit variation in the connection timing to the US railway network and shift-share variation in the location of immigrants across US counties to construct predicted county-level immigration shocks (Card, 2001; Sequeira, Nunn and Qian, 2020). We use these shocks to randomize British immigration across counties.

The main finding of this paper, which we label "return innovation," is that innovation in the UK is affected by exposure to US innovation through out-migration linkages. First, we document an increase in total patenting in districts with more US emigrants: moving from the 25th to the 75th percentile of US out-migration yields an 8% increase in the number of patents produced in the United Kingdom.

[4]Our core units of observation are UK registration districts and US counties. In 1901, there were 631 registration districts in England and Wales. Districts were comparable to US counties in population (approximately 40,000). Unlike counties, however, registration districts were statistical entities that did not enjoy political or budgetary autonomy.

Second, districts increase their innovation activity in the technological fields to which emigrants are exposed in the United States. Using an index that leverages joint variation in the location where emigrants settle and the innovation they are exposed to, we find that moving from the 25th to the 75th percentile of the "knowledge exposure" index is associated with an 11% increase in innovation activity. Third, we adopt a text-analysis methodology that computes the textual similarity between UK and US patents to measure the transfer of innovation generated by migration ties. We find that patenting in districts with more US emigrants becomes more similar to US patents: moving from the 25th to the 75th percentile of emigration to the US is associated with UK patents that are twice as similar to American ones. This effect also holds within technologies.

In the double differences regression, innovation in districts exposed to a US innovation shock through migration ties increases by 9%. A back-of-the-envelope calculation shows that migration ties generate a 15% pass-through rate of innovation shocks from the United States into the United Kingdom. In exposed districts, patents become substantially more similar in their textual content to American patents. These results also hold in the triple differences framework, which leverages shocks to US innovation activity across counties and technologies. A causal interpretation of the double and triple differences estimates requires that districts exposed to US innovation shocks and untreated districts would not have displayed differences in patenting activity in the absence of the shocks. Throughout the paper, we estimate event-study specifications and the pre-treatment coefficients are never statistically different from zero, thus supporting the parallel trends assumption.

The effects of exposure to foreign innovation are heterogeneous across sectors. In particular, we uncover an inverted U-shaped relationship between return innovation and the specialization of the UK relative to the US. In response to emigrants' exposure to US innovation, patenting in the UK increases the most in sectors where the US and the UK have similar specialization rates. By contrast, the effect is considerably smaller in areas where the US is more advanced, such as agriculture and metallurgy, and where the UK is more advanced, such as textiles. This pattern is consistent with the theoretical predictions of Van Patten (2023), who argues that the gains from international technology diffusion are highest when a country interacts with partners with higher but similar levels of development.

In the second part of the paper, we exploit the richness of our data to explore the mechanisms behind the return innovation effect. On the one hand, return innovation may require the physical return of migrants. On the other hand, migration ties may promote the diffusion of new technologies irrespective of physical return. We find that the physical return of migrants is an important driver of return innovation, but it does not explain it in full. Namely, return migration flows account for approximately half of the overall return innovation effect. However, the impact of exposure to

US innovation through out-migration remains sizable and significant even in the absence of return migration. This suggests that migration ties contribute to the diffusion of knowledge even without physical return.

First, we study the role of interactions between emigrants and their communities of origin as a driver of the diffusion of innovation. We focus on two factors that could promote such interactions: family ties and geographical proximity. Our analysis builds on a large literature in development economics which links the diffusion of technology to network interactions (e.g. Bandiera and Rasul, 2006; Conley and Udry, 2010; Beaman, BenYishay, Magruder and Mobarak, 2021).

We document that family members of US emigrants increase their patenting activity after their relatives moved to the US. It takes about ten years for a British emigrant to contribute to innovation activity back home. Despite this delay, the magnitude of the effect is large. Importantly, we can distinguish between emigrants who, at some point, return to the UK from those that do not. The impact of return emigrants is larger than those who never return. However, emigrants promote innovation in their families even if they never return. Since return emigrants account for approximately one-third of the entire migrant stock, the magnitudes of these effects are, in aggregate, similar.

As an alternative proxy for local social networks, we leverage the geographical proximity between emigrants and their former neighbors. To estimate its impact on the innovation activity of stayers, we link the UK patent data to the UK full census, and we geo-code information on the universe of the UK population. We find that patenting activity increases for non-migrants after their neighbors migrate to the United States.[5] The estimated effect remains positive and significant when we exclude the neighbors of return migrants, suggesting that cross-country interactions between emigrants and their origin communities are a key driver of return innovation.

Second, we study how migration ties interacted with information technologies to facilitate the flow of knowledge from the United States to the United Kingdom. We study the introduction of the first transatlantic telegraph cable connecting the US and the UK in 1866 as a sudden and sizable reduction in the cost of information transmission (Steinwender, 2018). Using a difference-in-differences framework, we show that districts with higher US emigration rates before the introduction of the transatlantic telegraph cable have higher patenting activity after 1866. Moreover, the gains in patenting activity are larger in those same technologies that districts had been more exposed to through migration ties. These findings suggest that the increased economic integration generated by the telegraph accrued relatively more to districts with pre-existing migration ties with the US market.

[5] In the baseline exercise, two individuals are considered neighbors if they live within five kilometers of each other. The results are very similar when the distance is between 3- and 10-kilometers.

To conclude the analysis, we examine whether information flows promoted by migration ties are specific to innovation. To answer this question, we study the effect of out-migration on newspaper coverage of US-related news in the United Kingdom. We collect data on the coverage of US-related news from a comprehensive repository of historical British newspapers. We find that newspapers in areas with more US emigrants are relatively more likely to cover US-related news. Coverage of a given state or county is higher in districts with more emigrants to that given state or county. This suggests that migration ties generate a flow of information that goes beyond the diffusion of new technologies.

This paper provides new evidence on how knowledge diffuses across countries. We document that exposure to foreign innovation through migration ties contributes to the diffusion of innovation from the country of destination to the country of origin of migrants. Taken together, our results suggest that out-migration can promote innovation by fostering the diffusion of knowledge into emigration countries.

Related Literature. This paper is related to four streams of literature. First, we contribute to the literature studying the dynamics and determinants of knowledge flows and technology diffusion across countries (among others, see Jaffe, Trajtenberg and Henderson, 1993; Griffith *et al.*, 2006; Bahar, Hausmann and Hidalgo, 2014). Specifically, we contribute to the papers documenting how human mobility fosters the diffusion of novel knowledge (e.g., Kerr, 2008; Hornung, 2014; Bahar, Hauptmann, Özgüzel and Rapoport, 2019; Bahar, Choudhury, Sappenfield and Signorelli, 2022; Prato, 2022). We contribute to this literature from several perspectives. First, we study the universe of emigrants instead of a selected subgroup of highly skilled individuals. Second, we leverage recent insights by Bell *et al.* (2019) and show that exposure to foreign innovation affects the diffusion of those technologies. Third, we emphasize that the return innovation effect does not exclusively hinge on the physical return of emigrants. Finally, our setting allows us to uncover the long-run effects of emigration and the mechanisms through which it affects innovation in the home country of emigrants.

Second, we contribute to the literature that studies the determinants of the direction of innovation and the allocation of research activity across technological sectors. Pioneering work on directed technical change was formalized by Acemoglu (2002, 2010). More recently, the question has been studied both theoretically (e.g., Bryan and Lemus, 2017; Hopenhayn and Squintani, 2021; Acemoglu, 2023) as well as empirically (e.g., Hanlon, 2015; Moscona, 2021; Moscona and Sastry, 2023; Einiö, Feng and Jaravel, 2023; Dossi, 2024; Truffa and Wong, 2024). We add to this literature by introducing one novel determinant of the direction of innovation, namely, international human mobility, through the return innovation effect.

Third, we contribute to the literature that studies the effects of out-migration on countries sending migrants. Emigration has been shown to impact wages (e.g., Dustmann, Frattini and Rosso, 2015), attitudes towards democracy (Spilimbergo, 2009; Batista and Vicente, 2011) and political change (Chauvet and Mercier, 2014; Karadja and Prawitz, 2019), technology adoption (Coluccia and Spadavecchia, 2024), entrepreneurship (Anelli, Basso, Ippedico and Peri, 2023), and social norms (Beine, Docquier and Schiff, 2013; Bertoli and Marchetta, 2015; Tuccio and Wahba, 2018). This paper provides new evidence that emigration shapes the rate and direction of innovation because it exposes emigration countries to novel knowledge produced abroad. These findings add to the existing literature, which generally interprets out-migration as a depletion of the stock of human capital.

Finally, by its setting, this paper adds to the literature that studies technical change and diffusion of novel technologies during the Age of Mass Migration. A growing number of papers examines the short-run (e.g., Moser, Voena and Waldinger, 2014; Arkolakis, Lee and Peters, 2020; Moser, Parsa and San, 2020) as well as the long-run (e.g., Akcigit, Grigsby and Nicholas, 2017; Burchardi, Chaney, Hassan, Tarquinio and Terry, 2020) implications of immigration on US innovation. This paper is closest to Andersson, Karadja and Prawitz (2022), who show that mass out-migration in Sweden triggered labor-saving innovation by increasing the relative cost of labor. In this paper, we document an entirely different phenomenon–the "return innovation effect"—whereby emigrants generate knowledge flows from where they settle towards their areas of origin. Our findings show that emigration promotes the cross-border diffusion of knowledge and investigate the underlying mechanisms.

Outline. The rest of the paper is structured as follows. In section II, we describe this study's historical and institutional context. In section III, we describe the data. In section IV, we present the empirical research design. In section V, discuss the main findings. In section VI, we discuss the mechanisms and possible alternative interpretations. In section VII, we conclude.

II Historical Background

In this section, we provide details on the English and Welsh migration to the United States (II.A) and on intellectual property protection in the United Kingdom and in the United States (II.B).

II.A The English and Welsh Migration to the United States

Between 1850 and 1920—the so-called Age of Mass Migration—more than 30 million Europeans migrated to the United States (Abramitzky and Boustan, 2017). Migrants from England and Wales accounted for approximately 10% of the total (Willcox, 1928), and emigration rates in Britain were among the highest in Europe (Baines, 2002).[6] In this section, we provide details on the English and Welsh migration to the US.

II.A.1 Migration Policy in the United Kingdom and the United States

Until 1917, the US applied minor restrictions on European immigration (Abramitzky and Boustan, 2017). This means that the Age of Mass Migration was characterized by virtually no legal constraints to human mobility to the US. Immigrants mostly originated from Northern Europe, particularly the United Kingdom, Ireland, Germany, Sweden, and Norway. This positive attitude towards immigration started to decline in the 1890s as flows from Eastern and Southern Europe increased. The restrictive immigration policies of the 1920s, however, allotted generous quotas to the United Kingdom, which were never filled (Abramitzky and Boustan, 2017).[7]

Like in other European countries, out-migration legislation in the UK encouraged emigration towards the Empire (Baines, 2002).[8] Emigration to the United States was neither subsidized nor discouraged. Attitudes towards out-migration remained positive after World War I. The perceived slowdown of emigrant flows after the War was viewed with concern by policymakers (Leak and Priday, 1933).

II.A.2 The Characteristics of British Emigrants

The British migration to the US presents two main distinctive features compared to the broader European phenomenon.[9] First, unlike most continental countries, Britain was already highly urbanized and industrialized at the inception of the Mass Migration. Starting in the 1880s, urban areas supplied most overseas migrants (Erickson, 1957, 1972; Thomas, 1954).

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[6]Only Ireland, Italy, and Norway had higher emigration rates, although, in England, massive out-migration spanned longer than in the other countries above.

[7]The 1921 (resp. 1924) Act computed the quota for a given country as 3% (resp. 2%) of the population from that country that was recorded in the US census in 1910 (resp. 1880). This scheme favored first-wave immigration countries, such as the United Kingdom and Germany, at the expense of new ones, as recommended by the Dillingham Commission (Higham, 1955).

[8]Out-migration was encouraged in two ways: reduced and subsidized ticket fares and allotment of agricultural lands. Policy efforts were directed towards the Empire, particularly Canada and Australia, through the Committee of the Emigrants' Information Office. In general, however, these policies were not successful. Baines (2002) argues that less than 10% emigrants traveled under government assistance during the entire 1814-1918 period, and Leak and Priday (1933) report similar figures for the post-War era.

[9]Throughout the period, the US was the most frequent destination for English and Welsh migrants. Between 1850 and 1930, more than 40% of total British and Welsh emigrants settled in the US. This compares to 25% in Canada, 20% in Australia, and 15% in other destinations (Baines, 2002).

Second, the selection of British migrants differed from that in continental Europe (Erickson, 1957). Compared to the occupational structure of Great Britain, migrants were less likely to be employed in agriculture and more likely to be low and high-skilled industrial workers (Baines, 2002, p. 83). Until the 1880s, British emigrants generally came from rural areas and, consequently, the vast majority were farmers. However, as cities and smaller urban centers gained prominence, migrants were increasingly employed in industrial manufacturing occupations. At the beginning of the 1860s, when the transatlantic migration was taking off, about 15% emigrants were employed in agriculture, and merely five percent were white-collar workers. In the early 1900s, however, this composition had shifted as agriculture workers accounted for a mere five percent of the overall emigrant stock, while those employed in white-collar occupations were 25%.

II.B Intellectual Property Protection in the United Kingdom and in the United States

During the period of our analysis, patents in the United Kingdom and the United States were granted by the respective patent offices. However, throughout the period, the UK and the US did not mutually recognize patents. In this section, we describe patent protection in the two countries, as well as international intellectual patent protection over this period.

II.B.1 Patent System in the United Kingdom

The United Kingdom established the world's oldest continuously operating patent system in 1623-1624. However, access to intellectual property protection was difficult until 1850 (Bottomley, 2014). Fees amounted to approximately four times the average annual income in 1860, and the application process was lengthy and uncertain (Dutton, 1984). A large literature documents the poor performance of this system during the Industrial Revolution (e.g., Macleod, 1988). The 1852 Patent Law Amendment Act sought to reform this process. The US system inspired the reform effort, which reduced application fees and shortened the bureaucratic process. A subsequent reform in 1883 further reduced fees and allowed applications by mail. This reform also introduced a litigation system and the employment of professional patent examiners. A technical examination of novelty was introduced only in 1902. Until 1907, patents were granted conditional on the invention being produced in Britain (Coulter, 1991).

II.B.2 Patent System in the United States

The first article of the United States Constitution establishes that inventors should be granted exclusive rights over their discoveries. In 1836, US Congress passed the Patent Act, which formally instituted the US Patent Office (USPTO). The USPTO has been credited as the first modern patent system in the world (Khan and Sokoloff, 2004). Two features distinguished the American patent system from its European counterparts. First, professional examiners carried out a novelty examination to ascertain the originality of patent applications. Second, low application fees ensured access to intellectual property protection was widespread.

II.B.3 International Intellectual Property Protection

As national patent systems were established in Europe and in the US during the 19$^{\text{th}}$ century, demands for international regulation increased. The Paris Convention—formally, the "Paris Convention for the Protection of Industrial Property"—of 1883 governed international patent protection (Penrose, 1951). This agreement emerged from a decade of multilateral confrontations that started with World Exhibitions in Vienna (1873) and Paris (1878). The Paris Convention introduced two major principles. First, nationals and residents of subscribing countries were guaranteed equality of treatment with nationals. This concept, known as "national treatment", rejects the principle of "reciprocity", which maintains that nationals in subscribing countries would be granted the same protection as their origin country. The United States strongly advocated for reciprocity (Penrose, 1951). Second, upon applying for a patent in a member country under Article 4, inventors were granted a "right of priority" of six months. Patents filed in foreign countries during the priority period would not invalidate the inventor's claim for protection in other member countries. However, patents obtained in one member state were *not* automatically recognized by other countries. To effectively claim protection, inventors had to submit different patent applications, which represented a substantial bureaucratic and financial burden. The UK joined the Convention in 1884, and the US joined in 1887.

While the Paris Convention—and its numerous amendments—are still in operation today, international patents were established in 1970. Since the UK and the US did not mutually recognize patents, we can use them as a proxy for knowledge flows between the two countries.

III Data

To conduct the analysis, we assemble two novel datasets. The first links British migrants in the United States to the UK census, allowing us to construct a matrix of bilateral migration flows at the UK district and US county level. This also provides individual-level information on the origin of migrants and allows us to build a dataset of return migrants. We describe this dataset in section III.A. The second dataset includes the universe of patents granted in England and Wales between the second half of the 19th century. We digitize these data, which to date were not available in disaggregated form, and link inventors to the UK census. We describe this dataset in section III.B. In section III.C, we describe the additional data sources we use in the analysis.

III.A A Novel Individual-level Dataset of British Immigrants in the United States

Our empirical analysis requires information on the origin of English and Welsh immigrants *within* the United Kingdom. The available data, however, do not contain this information. Neither the US nor the UK collected disaggregated records on the origin of immigrants and the destination of emigrants. We address this limitation by developing a new dataset that links British immigrants in the US to the British census. In this way, we are able to observe an individual in the US and to track him to his UK census record before he emigrated.[10] This is the first dataset that reconstructs migration flows at this granular level of aggregation for a non-Scandinavian European country during the Age of Mass Migration and adds to work by Abramitzky, Boustan and Eriksson (2014) Andersson *et al.* (2022) for Norway and Sweden.[11]

To construct the linked dataset, we leverage confidential individual-level data from population censuses in the United Kingdom (Schurer and Higgs, 2020) and the United States (Ruggles *et al.*, 2021). We extract the universe of British male immigrants from US censuses in 1900, 1910, 1920, and 1930.[12] These records contain the name and surname, birth year, and immigration year of each migrant. Using these variables, we match these individuals to the last British census where the emigrants appeared.[13] We use state-of-the-art census-linking algorithms adapted from pioneering work by Abramitzky, Boustan, Eriksson, Feigenbaum and Pérez (2021), as documented in appendix sections A.III.1 and A.III.2, which discuss in more detail the primary sources and the technical implementation of the algorithm.

In our preferred version of the data, we match approximately 65% of male British immigrants who

[10] Throughout the paper, we use the masculine to refer to individuals in our data because, as we explain in detail later, we can only work with male individuals.

[11] England and Wales were larger in terms of the overall population and US immigrant population. The population of Sweden and Norway in 1890 was approximately 4.7 and 2 million, while it was 27 million in England and Wales.

[12] We cannot use information from the 1870 and 1880 censuses because the immigration year was not recorded. Individual-level data from the 1890 census have not survived. Following the standard practice in the literature, we only link men because women usually changed their surname upon marriage.

[13] For example, we link an individual who immigrated to the US in 1905 to the 1901 UK census. Because no census was taken in 1870, we match those who migrated between 1870 and 1881 to the 1860 census. Moreover, since the last available UK census was in 1911, we match all those who emigrated after 1911 to that one. This implies that we have no information on migrants born after 1911. Since the median age of migrants is 30 and less than 10% of the distribution is younger than 19 in the rest of the sample, this bears little quantitative implications for the matching rate in the later part of the sample.

appear in the United States census, as shown in Appendix Figure A.9. The linking rate is considerably higher than benchmark datasets linking individuals over time (e.g., Abramitzky *et al.*, 2021). There are at least three potential explanations for this difference. First, British immigrants were a positively selected group of urban skilled manufacturing workers. Their census records would, therefore, plausibly be more accurate than for other populations.[14] Second, British immigrants spoke English. Linguistic factors do not threaten our linking algorithm, but they are challenging to resolve in intergenerational linking routines. Finally, the high quality of UK census records facilitates the linking procedure.

This approach nonetheless presents some important caveats.[15] First, it may deliver spurious links if the matching variables are insufficient to restrict the pool of potential matches. Second, the matching probability may be correlated with individual characteristics. To address the first issue, we discard the matches that do not attain a high level of string similarity. Moreover, we weigh each migrant by the inverse of the number of matches he is paired with to minimize the weight placed on false positive matches. In Table A.3, we report the correlation between emigrants' observable characteristics and the linking probability. Overall, this association is small and often statistically insignificant.

It is challenging to validate the data with external sources that contain disaggregated information on the origin of British emigrants to the US because, to the best of our knowledge, they do not exist. In Appendix Figure A.11, we correlate our data with county-level estimates of aggregate transatlantic emigration for the period 1880–1910 assembled by Baines (2002) and confirm that the two are positively correlated.[16]

In addition, we construct a dataset of return migrants. To assemble it, we apply the same logic as before. The only difference is that migrants are matched to the UK censuses taken in the decades *after* their immigration year. As an example, someone who migrated to the US in 1895 is matched to censuses in 1901 and 1911. To avoid double counting, if an individual is matched to more than one census, we keep the match(es) in the first.

Figure I reports in grey the number of English and Welsh immigrants in the United States by year of immigration, digitized from official statistics (Willcox, 1928). The blue line on the right y-axis tabulates the number of immigrants in our linked dataset. Our data co-moves with official statistics data. Figure IIa reports the spatial distribution of emigration rates across districts in the final sample

[14] This is in line with evidence by Helgertz, Price, Wellington, Thompson, Ruggles and Fitch (2022) that individuals with relatively higher socio-economic status have higher linking rates in the US census.

[15] Appendix Section A.III.3 presents a more detailed discussion of the internal and external validation exercises we undertake to assess the plausibility of the linked emigrant sample.

[16] See Appendix A.III for a more detailed discussion.

and highlights its cross-sectional spatial heterogeneity. In Appendix Figure A.12, we break down the map by decade and uncover substantial variation in the origin of US emigrants over time. We discuss this in detail in Appendix Section A.III. Table I, Panel A provides descriptive statistics for variables tabulated from the 1880 individual census. Panel B lists the district-level number of emigrants and return migrants in the UK-US-linked migrants sample by decade.

III.B A Dataset Covering British Patents in the Second Half of the Nineteenth Century

We measure innovation activity using patents, as standard in the literature (Griliches, 1998).[17] We use data on the universe of patents granted in the United States digitized by Berkes (2018). Leveraging information on the county of residence of inventors and the technology class (both reported on patent documents), we construct a balanced panel at the county-technology class-grant year level.[18]

We collect all the patents granted in the United Kingdom in 1900-1939 from PATSTAT, which provides bulk access to documents from the European Patent Office. These data contain information on authors and CPC classes but do not report the geographic location of inventors. To retrieve the coordinates of the inventors, we merge them with data by Bergeaud and Verluise (2024) and map them to registration districts at their 1890 borders.

For the period between 1853 and 1898, UK patent data was not available in digitized format. To tackle this data limitation, we digitize the universe of patents granted in England and Wales between 1853 and 1899 from scans of the original documents we obtained from the UK Patent Office (UK IPO). We apply optical character recognition (OCR) techniques on more than 300,000 original documents to convert the scanned images into machine-readable texts. Then, we use large language models to parse the information contained in the raw text into a structured dataset. Compared to standard text extraction algorithms, this method harnesses artificial intelligence to deal with OCR issues and non-standard formulations of patent texts.[19] We parse information on the title, text, inventors' names,

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[17] Patents are not a flawless measure of innovation because non-patented innovation represents a non-negligible share of overall technological progress (Moser, 2019). We nonetheless believe that this is a comparatively minor issue for our analysis. As discussed in section II.B, before our study period, the US and the UK had enacted important reforms that decreased the cost of access to patent protection. These drastically increased the number of patents in both countries, thus ensuring that patents convey an informative picture of the state of technology in both countries. In addition, our results also hold *within* technologies. Hence, if the propensity to patent in a given sector is similar in the UK and in the US, different propensities to patent across sectors should not be a concern for our analysis.

[18] We map patents to counties at 1900 borders. From the three-digit Cooperative Patent Classification (CPC) class, we map patents to a coarser taxonomy of twenty technological sectors.

[19] Appendix A.II provides more details on the implementation procedure of the OCR and parsing algorithms.

geo-referenced addresses, filing and issue dates, assignee status, and whether the patent was filed by a patent agent. To conduct the analysis, we map patents to districts at 1890 borders.

This dataset adds to the one developed by Hanlon (2016) (1855–1883) by adding information on patent titles, texts, and geography and extending the period until 1898, and expands previous work by Nuvolari and Tartari (2011), which covers the period until 1853. Figure A.4 reports the number of patents granted in the UK by year (Panel A.4a). The blue dots report the dataset we assemble, and the red data are tabulated from PATSTAT. The two series are consistent and display a steady growth in the number of patents issued throughout the period. Panel A.4b shows the evolution in the number of patents granted by technological class.

Patents differ by novelty and economic value. In contemporaneous settings, patent forward citations are the standard proxy for patent impact. However, these were not reported in historical documents (Andrews, 2021). To construct a measure of patent "impact," we apply the text-based methodology developed by Kelly, Papanikolaou, Seru and Taddy (2021) to the corpus of British patents. Additionally, we use the same methodology to measure the textual similarity between British and American patents and proxy for technology transfer between the US and the UK. Appendix A.II.6 describes in detail the practical implementation of the algorithm.

Finally, to perform the neighborhood-level analysis, we link the patent data to the census. To perform this linking, we match inventors based on the string similarity between their name and surname and those recorded in the census, conditional on geographic proximity. We describe the precise implementation in Appendix section A.II.7. Figure A.8 displays the geographic distribution of inventors across England and Wales using the geo-coded addresses of the inventors linked to the census. The map highlights that most innovation happens in urban centers.

In Table I, Panels C and D, we report descriptive statistics for this sample. Panel C reports the total number of patents granted across districts by year and breaks it down into the five most common fields in the sample. Panel D reports statistics for the sample of inventors linked to the population census. Figure II, Panel IIb reports the spatial variation in number of patents normalized by district population in 1891.

III.C Additional Variables

To conclude this section, we provide details on the additional variables that we construct from existing sources. Specifically, we collect data on UK district-level statistics, on British local newspapers, and on the telegraph network in the UK.

III.C.1 Data Constructed from the British Population Census

We assemble district-level statistics from UK population censuses at a decade frequency between 1851 and 1911. Districts are the level of observation in most of the analysis. This is because they were statistical units with an average population of 40,000, which makes them broadly comparable to US counties.[20] Districts undergo minor boundary changes during the analysis period. To ensure geographical consistency, we cross-walk all variables to districts in 1890 (see Appendix A.I.6).

III.C.2 Newspapers

We use newspaper coverage of US-related topics as a measure of attention to the United States in public opinion. We collect the data from the British Newspaper Archive. Beach and Hanlon (2023) discuss this dataset in detail. We run three sets of queries. First, we search for the joint mention of the words "United States"; second, we search for mentions of each US state; third, we search for mentions of each US county, jointly with either the state name or "United States". We collect these data at the newspaper level from 1850–1939. Additionally, we know each newspaper's publishing address, which we geo-reference to 1890-border districts. Ultimately, we assemble three datasets at the district, district-state, and district-county levels, each at decade frequency. Figure A.2 reports the distribution of newspapers, and Table A.4 provides descriptive statistics on their activity.

III.C.3 Telegraph Network

We reconstruct the English and Welsh telegraph network from *Zeitschrift des Deutsch-Österreichischen Telegraphen-Vereins, Jahrgang*, volume IX, 1862. This directory lists all telegraph stations outside of London in 1862. To the best of our knowledge, it is the most comprehensive list before the establishment of the transatlantic telegraph cable connecting the UK and the US (1866). We geo-reference all the stations and assign them to 1890-border districts. Since the source does not list stations in the London area, we conflate London urban districts into a single "London," which we assume to be connected to the telegraph network. Figure A.1 reports the distribution of the stations.

IV Empirical Strategy

In this section, we describe our empirical strategy. In subsection IV.A, we provide details on the construction of technology exposure in the United States. In subsection IV.B, we outline our baseline empirical specifications and discuss the potential endogeneity associated with them in subsection

[20] Differently from US counties, UK districts did not have budgetary or administrative authority.

IV.C. In subsection IV.D, we outline our identification strategy and the associated double and triple differences designs.

IV.A Measuring Exposure to American Technology

We construct two measures of exposure to US technology. The first is the number of emigrants to the United States from any given UK district. The underlying hypothesis is that districts with relatively more emigrants to the United States have higher exposure to US technology.

The second measure uses two margins of variation: along technological classes and along districts. First, local specialization across counties measures the knowledge that diffuses from those counties. Second, the number of migrants that leave a given district and settle in a given county measures the intensity of the return knowledge channel. To fix ideas, consider two districts and call them A and B. The same number of emigrants n leaves each district. Emigrants from A settle in county a, which only produces innovation in sector s_a. Emigrants from B settle in county b, which only innovates in sector s_b. Then, we expect district A (resp. B) to innovate comparatively more in sector s_a (resp. s_b).

We define knowledge exposure as:

$$\text{Knowledge Exposure}_{ik,t} \equiv \sum_{j \in J} \left(\frac{\text{Patents}_{jk,t}}{\text{Patents}_{j,t}} \times \text{Emigrants}_{i \to j,t} \right), \tag{1}$$

where i, j, k, and t denote a (UK) district, a (US) county, a technology class, and a decade, respectively.[21] The set J denotes the universe of counties. The knowledge exposure term averages district-level exposure to county-level specialization across technology classes.

The first term in the summation captures specialization, while the second term captures district-level exposure. The relative share of patents may inflate the influence of specialization in counties with a small number of granted patents. While this bias is unlikely to be large as those counties would likely have low district-level exposure, we code an alternative knowledge exposure variable that measures specialization as the raw count of patents in a given technology class. An additional challenge is that districts with larger bilateral linkages are probably larger and, hence, selected. To account for district-level time-varying confounding variables, we control non-parametrically for district-by-time fixed effects. However, we also report results for an alternative knowledge exposure that measures exposure through relative emigrant shares. We discuss these alternative definitions in more detail in the Appendix Table C.I.2.

[21] Throughout the paper, we refer to decade t to mean the ten years before the upper bound t. Hence, the decade indexed by 1890 refers to 1881–1890.

IV.B Empirical Specifications

We estimate two sets of regressions. First, we consider a specification that relates the volume of patenting activity in the UK with the number of transatlantic emigrants:

$$y_{i,t} = \alpha_i + \alpha_t + \beta \times \text{US Emigrants}_{i,t} + X_{i,t}\Gamma + \varepsilon_{i,t}, \tag{2}$$

where i and t denote, respectively, a district and a decade; $y_{i,t}$ is the outcome variable; α_i and α_t are district and decade fixed effects; US Emigrants$_{i,t}$ is the number of emigrants to the United States from district i between years $t-9$ and t; and $X_{i,t}$ is a set of district-level controls—population, employment shares across sectors, share of males—measured in 1880 and interacted with year dummies. Standard errors are clustered at the district level.

The second specification correlates patenting in the UK across technologies with the measure of exposure to US technology in (1):

$$y_{ik,t} = \alpha_{it} + \alpha_k + \beta \times \text{Knowledge Exposure}_{ik,t} + \varepsilon_{ik,t}, \tag{3}$$

where k denotes technology classes, the term α_{it} denotes district-by-decade fixed effects whose inclusion allows to control non-parametrically for time-varying unobserved heterogeneity at the district level; the term α_k denotes technology-fixed effects and excludes variation arising from factors that are technology-specific but common across areas and over time. Standard errors in this specification are clustered two-way at the district and technology level.

We consider three different sets of outcomes throughout the paper. First, we use the log(1+) number of patents to measure the volume of patenting activity. Second, to account for heterogeneous novelty across patents, we compute the log(1+) number of patents in the top 20% of the impact distribution of the measure constructed by Kelly *et al.* (2021) and applied to the corpus of UK patents. Third, to measure technology flows from the US into the UK, we compute the average text-based similarity between US and UK patents (Appendix A.II.6 provides additional details). In Appendix C.I.1, we present alternative specifications with different transformations and definitions of all the dependent variables and show that results remain qualitatively unchanged.

IV.C Potential Sources of Endogeneity

The main factor that cautions against a causal interpretation of the estimates of regression (2) is that out-migration is not random across districts. In particular, any unobserved variable correlating with out-migration and the volume of innovation y induces bias in the estimated β coefficient. To address this issue, in (3), we include district-by-time fixed effects to partial out time-varying heterogeneity within districts. This allows us to exclusively leverage cross-technology variation. A remaining potential issue is assortative matching, meaning there may be a—possibly unobserved—variable that correlates with the location where emigrants settle in the United States and the composition of patenting activity across technology classes.

In section II.A, we discussed that the historical and empirical evidence suggests that, over time, emigrants originated from increasingly affluent and urbanized areas. Suppose emigrants also settled in comparatively more urban and affluent counties in the United States, and there was a correlation between patenting activity in specific fields and economic growth. In that case, the selection issue may bias the OLS estimates upward. We note that the bias arises only if (i) the correlation between patenting and the underlying confounding variable is heterogeneous across technology classes and (ii) the correlation is similar in the US and the UK. If (i) does not hold, then the omitted confounding variable would be absorbed by district-by-time fixed effects. If (ii) does not hold, the selection bias would work against our result.

Assortative matching may also arise if pre-existing differences in specialization across technology classes predicted the counties where emigrants chose to settle. For example, suppose that emigrants from a largely textile area, say Lancashire, were comparatively more likely to settle in counties with larger textile sectors. Then, the estimated β from equation (3) would reflect pre-existing innovation similarities between sending and settling areas rather than capture the effect of return innovation. Evidence by Hanlon (2018) and Ottinger (2020), among others, suggest that location decisions may not be random. In Appendix Section B.III, we show that British migrants in this period do not display a similar pattern.[22] However, ultimately, we cannot rule out assortative matching across US counties.

In Online Appendix section C.I.4, we implement two instrumental variable approaches following the migration literature to rule out that assortative matching is generating our results. We exploit conditionally exogenous variation in the location of British emigrants across the United States. This allows us to construct valid instruments for emigration and exposure to US technology through migration ties.[23]

[22] Appendix Table B.3 presents evidence against this pattern.

[23] The first instrument uses the expansion of the railway network in the United States over the course of the 1800s to predict county-level immigration, building on Sequeira *et al.* (2020). The second instrument builds on Card (2001), and constructs predicted county-level immigration by interacting county-specific inflows of British immigrants at baseline with aggregate immigration inflows in the United States.

IV.D Isolating the Effects of Exposure to American Technology: Double and Triple Differences Analysis

To estimate the causal impact of immigrants' exposure to US technology on innovation in the United Kingdom, we leverage shocks to US innovation activity to randomize the volume and content of innovation that emigrants are exposed to.

Suppose we observe a sudden increase in the number of patents granted in some counties in a technology class. Then, the "return innovation" effect would imply that districts with more emigrants to those counties would display increased innovation activity in that class. In other words, innovation shocks in the United States should "reverberate" in the United Kingdom through pre-existing migration linkages.

We label any period of unusually high patenting activity as a "shock" to US innovation. As in the previous analysis, shocks can pool technologies together or be technology-specific. In the former case, to isolate the shocks, we residualize the (log) number of patents against county and year-fixed effects and label as a shock any observation whose residualized patenting activity is in the top 5% of the overall distribution. In the latter case, we residualize patenting against a fully saturated set of county, technology, and year-fixed effects and similarly tag as a shock any observation whose residualized patenting activity is in the top 5% of the overall distribution. From the perspective of US counties, innovation shocks are periods of unusually high patenting activity. In Appendix Table C.12 and Appendix Figure C.12, we report the difference-in-differences estimated increase in patenting associated with the shocks. Patenting increases by 58% (in the pooled case) and by 13% (in the technology-specific instance) after a shock.

Let $\sigma_{j,t}$ be an indicator variable equal to one if county j undergoes an innovation shock in year t. Similarly, let $\sigma_{jk,t}$ be an indicator equal to one if the county-technology pair ik undergoes a shock in year t and zero otherwise. To construct a binary indicator of exposure to these shocks across British districts, we first compute the number of emigrants from district i that are exposed to a shock as $\sum_{j\in J}\left(\text{Emigrants}_{i\to j}\times\sigma_{j,t}\right)$, where the term $\text{Emigrants}_{i\to j}$ is the number of emigrants who moved from district i to county j in the decade 1870–1879, and we residualize the resulting series against district and year fixed effects. Then, we define a district as exposed to an innovation shock if the residual of this regression is in the top 5% of the overall distribution of residualized emigrants exposed to innovation shocks. Let the indicator variable ξ_i be equal to one in the first period when district i is exposed to a US innovation shock and zero otherwise.[24]

[24] The technology-specific case follows the same logic. We compute the number of emigrants from district i that, in year t, are exposed to US innovation shocks in technology k as $\sum_{j\in J}\left(\text{Emigrants}_{i\to j}\times\sigma_{jk,t}\right)$. We residualize the resulting

Given a set of district-level shocks ξ_i and district-technology-level shocks ξ_{ik}, we estimate double and triple differences regressions to study how exposure to US innovation shocks impacts innovation in the UK. In the case of district-level shocks, the regression is as follows:

$$y_{i,t} = \alpha_i + \alpha_t + \sum_{h=-a}^{b} \beta_h \times I\left[D_{i,t} = h\right] + \varepsilon_{i,t}, \tag{4}$$

where t now denotes years and $D_{i,t} \equiv (t - \xi_i)$ is the number of periods since district i is first exposed to a US innovation shock ξ_i and $I[\cdot]$ is an indicator variable which is equal to one when the argument is true and zero otherwise. In the case of technology-specific shocks, the regression is a triple-differences model that reads out as:

$$y_{ik,t} = \alpha_{ik} + \alpha_{it} + \alpha_{kt} + \sum_{h=-a}^{b} \beta_h \times I\left[D_{ik,t} = h\right] + \varepsilon_{ik,t}, \tag{5}$$

where α_{ik}, α_{it}, and α_{kt} denote, respectively, district-by-technology, district-by-year, and technology-by-year fixed effects, and $D_{ik,t} \equiv (t - \xi_{ik})$ denotes the number of years since the district-technology couple ik is first exposed to a US innovation shock ξ_{ik}.

Under a standard parallel trends assumption, in equations (4)–(5), the coefficients $\beta_{h\geq 0}$ estimate the dynamic treatment effects of exposure to US innovation shocks on outcome y. The parallel trends assumption requires that, in the absence of the shocks, the outcome variable y would not have differed across treated and untreated units. While this assumption is not testable, we show that, in all regressions, the estimates of the pre-treatment coefficients β_h for $h < 0$ are never statistically different from zero. This consistent pattern provides evidence in favor of the plausibility of the parallel trends assumption.

The roll-out of shocks across units is staggered: different districts and district-technology pairs may be exposed to US innovation shocks at different moments. Goodman-Bacon (2021) shows that, in these settings, the two-way fixed-effects estimator fails to estimate the average treatment effect when treatment effects are heterogeneous. In robustness check, we employ the estimator proposed by Sun and Abraham (2021) to deal with the staggered nature of the research design and confirm all the baseline results. Moreover, we show that the results are not sensitive to alternative thresholds to define the shocks to US innovation or the district-level exposure to such shocks. We discuss robustness exercises more in detail in Section V.

series against district, technology, and year-fixed effects, and we tag an observation as a shock if the residualized value is in the top 5% of the overall distribution of exposure. Then, let ξ_{ik} denote the associated indicator variable equal to one the first year when the district-technology pair ik is exposed to a US innovation shock and zero otherwise.

V Main Results

In this section, we document our main result: the "return innovation" effect. Section V.A provides descriptive evidence on the association between exposure to innovation in the United States through out-migration and innovation in the United Kingdom. In section V.B, we provide causal evidence of the return innovation effect. Finally, in section V.C, we document that the effect is stronger in sectors where the US and the UK have similar relative specialization.

V.A Exposure to Innovation in the United States and the Volume and Direction of Innovation in the United Kingdom

We begin by studying the association between out-migration to the United States and patenting activity in the United Kingdom. In Table II, column (1), we report the estimates of equation (2). The coefficient reports the association between the log(1+) number of patents and the number of US emigrants (in thousands) over time across registration districts. We find a positive and statistically significant association between the two variables: moving from the bottom 25th to the top 75th percentile of the distribution of emigrants is correlated with an 8% increase in patenting activity in the district of origin. The magnitude of the coefficient halves but remains statistically significant when we include district-level controls interacted with time fixed effects (column 2).

In column (3), we provide a first test that the shift in innovation activity may come from increased exposure to US innovation through emigration. The outcome variable is the average text-based similarity between US and British patents issued in a given district and decade. We find that out-migration to the US is associated with a large increase in the average similarity between British and American patents. Moving from the 25th to the 75th percentile of out-migration is linked to a doubling of average similarity. We interpret this result as the first piece of evidence in favor of the initial hypothesis that emigrants foster the transfer of technologies from the US into the UK.

In column (4), we report the results of estimating equation (2) on the log(1+) number of patents in the top 20% of impact. We adopt the methodology introduced by (Kelly *et al.*, 2021), and we apply it to the texts of British patents. This measure flags more "impactful" patents whose text is distant from existing patents at the time of issue but similar to those issued afterward. We use a 5-year window to compute this similarity metric, but the results are not sensitive to alternative bandwidths. Using this measure, we verify that the effect of emigration on innovation is not entirely composed of low-impact innovations. In fact, moving from the 25th to the 75th percentiles of out-migration is associated with an 11% increase in the number of breakthrough patents.

These results may not have a causal interpretation because of omitted factors that are time-varying within districts and correlate with both out-migration and innovation, as discussed in section IV.C. To address this concern, we adopt two instrumental variables approaches: a railway and a leave-out instrument for emigration and innovation exposure. The results, reported in Panels B and C of Table C.2, confirm the OLS estimates.

In columns (5–8) of Table II, we study the link between exposure to US technology and the direction of innovation in the United Kingdom. In this case, district-technology class pairs are observed at a decade frequency. The baseline regression, shown in column (5), includes district-by-time and technology class-fixed effects. The coefficient in equation (3) reports the association between changes in exposure to US innovation by technology and innovation in the United Kingdom. We uncover a positive and statistically significant correlation between innovation exposure and innovation. Moving from the 25th to the 75th percentile of innovation exposure is associated with an 11% increase in patenting activity in that technology class. In column (6), we saturate regression (3) with a full set of fixed effects and confirm that the correlation remains positive and statistically significant.

As with overall innovation, in column (7), we show that exposure to US technologies is associated with an increase in the similarity between British and American patents. Quantitatively, the association is large, as moving from the bottom 25th to the top 75th percentile of the main regressor is associated with a three-fold increase in the average similarity between UK and US patents. In column (8), we confirm that the association between exposure to US innovation increases and patenting remains positive, statistically significant, and quantitatively unchanged when the dependent variable only includes patents in the top 20% of the impact distribution.

As discussed in section IV.C, these estimates may not have a causal interpretation if there is an omitted term that predicts where British immigrants settled across the United States and is correlated with the direction of innovation in their areas of origin. We refer to this issue as "assortative matching." Table C.2 reports the IV estimates for the district-technology sample. These are consistent with the OLS results, suggesting that assortative matching is unlikely to drive the results.

Finally, we explore the long-run association between exposure to US technology through emigration and innovation. Using data on patenting activity between 1940 and 2015, we compute the association between knowledge exposure in the 1930s and innovation in the later twentieth century. The association between knowledge exposure and innovation remains stable until the 1960s. It starts to decline in the 1970s, but the pace accelerates in the 1980s, and it never recovers. We then repeat the exercise but report the time-varying correlation separately for each sector. The impact of exposure to US technology through emigration ties thus retains an enduring impact on innovation dynamics in England and Wales, which persists well into the second half of the twentieth century. Appendix Section B.II provides a detailed discussion of this analysis.

V.B The Impact of Innovation Shocks in the United States on Innovation in the United Kingdom

In this section, we describe the results of estimating the double and triple differences research design described in Section IV.D. This enables us to draw a causal link between exposure to US innovation via migration ties and the volume and direction of innovation in the UK.

We begin by studying the impact of US innovation shocks on the volume of innovation in the UK. Column (1) of Table III reports the baseline estimate of regression (4), where we aggregate all pre- and post-treatment periods into two bins, and the treatment is equal to one after a given district is exposed to a US innovation shock and zero otherwise. After the district is exposed to a shock, patenting increases by approximately 9%. As shown in Table C.12, in the United States, an innovation shock is associated with a 58% increase in patenting activity in the county where it occurs. Hence, on average, emigration ties generate a 15% pass-through rate of innovation shocks from the US to the UK. Following a US innovation shock, the similarity between patents granted in exposed districts and American patents doubles (column 2). In addition, in column (3), we show that the number of patents in the top 20% of the impact distribution also increases—by 8.2%—in response to US innovation shock, implying that emigrants facilitate the transfer of high-quality patents from the US into the UK.

In columns (4–6), we report the estimates associated with regression (5), where again we conflate pre- and post-treatment periods into two single categories, and the treatment is an indicator that returns one after a district-technology class pair is exposed to a US innovation shock and zero otherwise. In this case, the regression includes the interactive fixed effects. Hence, identification hinges on within-district-technology exposure to US innovation shocks over time. The results confirm the previous findings. Innovation increases by 6% in districts exposed to an innovation shock. In this setting, emigrant ties generate a 50% pass-through rate of the increased patenting activity in the US into the UK. Patents in the same technologies and districts that are exposed to US innovation shocks also become more similar in their textual content to American patents. Finally, in column (6), we confirm that the results are quantitatively similar if we only include highly original patents in the dependent variable, as the number of patents in the top 20% of the impact distribution increases by 5% when units are exposed to the treatment.

Figure III reports the event-study estimates associated to model (4) (Panel IIIa) and (5) (Panel IIIb). In both cases, we find no evidence of statistically significant pre-treatment coefficients. In each Figure, we test for the joint significance of all pre-treatment coefficients and find no statistical support for the alternative hypothesis that there is at least one significant pre-treatment coefficient. Overall, we interpret these patterns as evidence in favor of the parallel trends assumption stated in IV.D. After the treatment, the number of patents increases. In fact, essentially all post-treatment coefficients are highly statistically—and jointly—significant. The exposure to US innovation shocks has a persistent impact on UK patenting. As shown in Figure C.6, patenting activity in the US increases sharply after a shock, but it remains significantly above the pre-shock mean after the shock period. The persistent effect observed in the UK is consistent with this pattern.[25]

In Figure IV, we re-estimate models (4) (Panel IVa) and (5) (Panel IVb) using the similarity between British and American patents as the outcome variable. As before, we estimate no statistically significant pre-treatment coefficient, except a ten-year lead in IVa. The tests for the joint significance of all pre-treatment coefficients provide further evidence in favor of the validity of the pre-trend assumption. After the shock, British patents in exposed units become more similar to American patents. The effect persists until ten years after the shock occurs. As in the previous case, the effect of the shock exhibits substantial persistence because the shocks are themselves persistent within counties.

V.C Return Innovation and Relative Specialization

To conclude this section, we study how the magnitude of return innovation changes by technology. Anecdotal evidence suggests the US was relatively more specialized than the UK in agricultural and heavy machinery technologies even early in the sample period, whereas the UK was more specialized in chemical and textile innovation (David, 1966; Rosenberg, 1970). To measure relative specialization across technologies, we build on the international trade literature and construct a measure of revealed comparative advantage (RCA). This index takes a value above one for technologies where the UK was more innovative than the US in terms of share of total patents, and below one otherwise (Balassa, 1965).[26] To study the heterogeneous responses to emigrants' exposure to US technology, we estimate equation (3) interacting knowledge exposure with a set of technology dummies. In Panel Va of Figure

[25] It is also plausible—although we do not test this hypothesis—that, after a shock, new technological advances are more salient to British immigrants, thereby amplifying the initial effect of the shock.

[26] In the international trade literature, the revealed comparative advantage is a metric that hinges on the observation that a country's comparative advantage is revealed by the country's relative exports (Balassa, 1965). In our setting, we define the revealed comparative advantage as

$$\mathrm{RCA}_{ik} \equiv \frac{\mathrm{Patents}_{ik} / \sum_{k' \in K} \mathrm{Patents}_{ik'}}{\sum_{i' \in I} \mathrm{Patents}_{i'k} / \sum_{i' \in I, k' \in K} \mathrm{Patents}_{i'k'}}$$

where i and k denote countries and sectors within sets I and K. Specifically, $I = \{\mathrm{UK}, \mathrm{US}\}$. Then, the UK is relatively more specialized in sectors with $\mathrm{RCA}_{\mathrm{UK},k}$ above one.

V, each dot reports the coefficient of one technology class on the y-axis, and the UK revealed comparative advantage for that class on the x-axis. We uncover an inverted U-shaped relationship between the size of return innovation and specialization. Exposure to US innovation generates larger gains in technologies where the US and the UK have similar rates of specialization, such as electricity, scientific instruments, and engines. By contrast, the gains are considerably smaller, and often not significant, in areas where the US is more advanced, such as agriculture and metallurgy, and where the UK is at the frontier, specifically textiles. The Figure reports the coefficients of a regression between the coefficients, the RCA, and its squared values and confirms the existence of such a hump-shaped relationship. This finding is consistent with the theoretical argument of Van Patten (2023), who develops a model of endogenous technology adoption where the gains from international technology diffusion are highest when a country trades with partners with higher—but similar—levels of development.

In Panel Vb, we repeat this exercise using the triple-differences regression (5). In particular, we interact the treatment with technology-specific dummy variables. Each dot reports, on the y-axis, the estimated treatment effect for one technology class. The coefficients are plotted against the measure of revealed comparative advantage. The resulting plot exhibits a pattern that largely resembles Panel Va. Exposure to US innovation shocks generates larger increases in patenting activity in the UK in fields with an RCA closer to one, namely, those where the UK and the US are equally active. By contrast, the treatment effect is zero—or negative, albeit negative estimates are never statistically significant—in fields where the US is more active than the UK, such as agriculture, and the reverse, such as textiles and chemistry.

V.D Robustness Checks

To conclude, we describe a series of checks that we perform to test the robustness of our results.

In the baseline analysis, our baseline measure of patenting is the log of the number of patents to which we add one to avoid dropping the zeros. In Tables C.1, C.2, and C.10, we show robustness to alternative transformations of the dependent variable for the OLS-2SLS (2)–(3) and the double and triple differences regressions (C.7)–(5) and find that all results remain qualitatively and quantitatively unchanged using the raw count, the inverse hyperbolic sine, or adding 0.1 instead of one to the log of the count. Moreover, Panels B and C replicate all specifications using the two instruments described in Appendix Section C.I.4. In Appendix Table C.5, the baseline equation (2) is estimated using the Poisson quasi-maximum likelihood estimator described in Correia, Guimarães and Zylkin (2020), which confirms the results.[27]

[27] We prefer a log-linear to a Poisson specification as the baseline because it allows us to test for robustness to potential concerns such as spatial autocorrelation, which would be hard to address with a Poisson regression.

In the baseline analysis, the text-based measures—similarity and originality—are computed over a five-year window around the issue year of the patent. In practice, this window implies that, when computing the originality of a given British patent, we compare it with those issued in the preceding and following five years. When computing the similarity between a British patent and other US patents, we consider those issued in the preceding five years. This is an arbitrary choice, hence in Tables C.1, C.2, and C.10, we consider two additional windows—one and ten years—and find that all the baseline results remain qualitatively unchanged.

In all specifications, when we look at district-level outcomes, standard errors are clustered at the district level. When the outcome is at the district-technology field level, we adopt two-way clustering by district and technology. In Figures C.1 and C.5, we use a set of alternative standard errors for both OLS-2SLS and double and triple differences regressions. In particular, we confirm that the results remain statistically significant when accounting for spatial autocorrelation as suggested by Conley (1999).

A possible concern with patents as a proxy for innovation is that they do not adequately reflect economically relevant innovations, i.e., technologies that are concretely adopted by firms. To address this concern, in Table C.3, we replicate the baseline findings of regressions (2)–(3) using as outcome variable only patents with a firm assignee. By law, the inventor of a patent in the UK—as in the US—must be an individual. However, many patents indicate when the inventor is employed in a firm or whether they are the owner. These patents provide an arguably more direct measure of firm innovation. All results hold when applying this sample restriction.

In Table C.4, we show that the baseline association between patenting and exposure to US technology remains qualitatively unchanged when using several alternative definitions of exposure, as detailed in C.I.2.

In the double and triple differences analysis, the roll-out of the innovation shocks across units in the double and triple differences models is staggered because they occur at different moments across districts and technologies. Following the literature, in Figure C.3, we replicate the baseline results obtained using the standard two-way fixed-effects estimator using the framework developed by Sun and Abraham (2021). We obtain very similar results when using the log(1+) number of patents (Panels C.3a–C.3b) and the similarity between British and American patents (Panels C.3c–C.3d) as outcome variables.

In Figure C.4, we replicate the baseline event studies but estimate the specifications (4)–(5) as Poisson quasi-maximum likelihood regressions. The estimates confirm the baseline results: we find no evidence of statistically significant pre-treatment coefficients, and innovation increases after UK districts are exposed to shocks to US innovation.

Finally, in Section IV.D, we explain how we construct the treatment in the double and triple differences models. In both cases, we define a unit—either a district or a district-technology pair—as exposed to a US innovation shock in a given period if the number of migrants who are exposed to a US innovation shock from that district is in the top 5% of the overall distribution of exposed emigrants. The underlying logic is that a unit is exposed if a "sufficiently large" number of emigrants from that place is, in turn, exposed to a US innovation shock where they are settled. The 5% threshold is arbitrary. In Table C.11, we adopt two alternative definitions of the shocks (top 10% and top 1%). Intuitively, more restrictive thresholds should deliver larger treatment effects because they require more emigrants to be exposed to a US innovation shock to activate the treatment at the district level. The estimates confirm this insight: while most of the coefficients remain statistically significant irrespective of the threshold, the magnitude of the estimated treatment effect increases with more restrictive thresholds.

VI Mechanisms

After documenting the "return innovation" effect, we study its drivers. In section VI.A, we show that return migration accounts for approximately half of the overall effect. In section VI.B, we document that, even in the absence of return migration, emigrants impact the innovation activity of their social networks in the United Kingdom. In section VI.C, we study the introduction of the transatlantic telegraph cable and document that lower communication costs fostered return innovation. Additionally, we show that out-migration fostered a flow of information beyond the diffusion of new technologies, as local newspapers in the UK were more likely to mention the counties with high out-migration from the given UK district (section VI.D). Finally, in section VI.E, we discuss potential alternative mechanisms that cannot be tested empirically.

VI.A The Role of Return Migration

Return migration is a primary candidate for explaining our findings through two channels. First, return migrants may engage in innovation activities in the fields they were exposed to abroad. Second, return migrants may facilitate access to US knowledge without directly undertaking innovation activities. The literature does not offer conclusive evidence on the effect of return migration on innovation (e.g., Giorcelli, 2019; Ash, Cai, Draka and Liu, 2022).

The baseline linked sample of British emigrants traces them back to the UK census before they migrated. To measure return migration, we instead link them to UK censuses completed after they had migrated to the US. Then, we aggregate return migration flows at the district-by-county level and at decade frequency. Analogously to equation (1), we compute a measure of "return knowledge exposure" as follows:

$$\text{Return Knowledge Exposure}_{ik,t} \equiv \sum_{j \in J} \left(\frac{\text{Patents}_{jk,t}}{\text{Patents}_{j,t}} \times \text{Return Migrants}_{j \to i,t} \right) \tag{6}$$

where Return $\text{Migrants}_{j \to i,t}$ is the number of migrants that return from county j to district i in decade t. Because UK censuses are available only until 1911, return migration data span 1870–1910.

Table IV reports the results of two classes of regressions which mirror specifications (2)–(3), except that we include returning US emigrants (columns 1–3) and the return knowledge exposure indicator (columns 4–6), at different lags. Throughout the specifications, the coefficients of US emigrants and the baseline knowledge exposure metric remain statistically significant. By contrast, the association between return migrants, return knowledge exposure, and patenting is less clear. It is mostly positive, as one would expect, but it is often not significant. Quantitatively, moving from the 25th to the 75th percentile of out-migration—resp. knowledge exposure—in column (1)—resp. column (4)—is associated with a 5.2%—resp. 7.1%—increase in patenting activity. By comparison, shifting by the same amount along the distribution of return emigration—resp. return knowledge exposure—yields a 3.8%—resp. 3.7%—increase in patenting. Overall, while we document a positive correlation between return migration and patenting, it appears that there remains substantial variation in innovation associated with out-migration that is left unexplained by return flows.

In the rest of the paper, we provide evidence of two additional mechanisms explaining the return innovation effect, which do not rely on return migration. First, we focus on the interactions between the emigrants and local communities in Britain. Second, we explore how information technologies interacted with migration ties to promote the diffusion of knowledge.

VI.B The Role of Social Networks

In this section, we study how emigrants impact the innovation activity of their social network in Britain. We focus on two factors promoting interactions between the emigrants and the non-migrant population: family ties and geographical proximity. This analysis builds heavily on experimental evidence from developing countries, which links the diffusion of technology to interactions over social networks (e.g., Bandiera and Rasul, 2006; Conley and Udry, 2010; Beaman *et al.*, 2021)

VI.B.1 Transatlantic Emigration Within Families

To reconstruct extended families from the census data, which only contains information on the members of the same household, we leverage the geographical distribution of surnames. Specifically, we assume that individuals with the same surname who live in geographical proximity—in the same county—are related. This assumption is reasonable as long as surnames are not too common: in this analysis, we, therefore, drop the top 5% most common surnames. Results are robust to alternative samples excluding the 1% or 10% most common surnames.

We study how US emigration impacts the innovation activity produced by the relatives of the migrants who do not move in a difference-in-differences setting. The treatment leverages variation in the surname of US emigrants by county. Formally, we estimate variations on the following regression:

$$y_{f,t} = \alpha_f + \alpha_t + \sum_{h=-a}^{b} \beta_h \times I[D_{f,t} = h] + \varepsilon_{f,t}, \tag{7}$$

where f denotes a family—i.e., a surname-by-county pair—and t is a year. The term $D_{f,t}$ denotes the number of periods since at least one member of family f moved to the United States. Since families are identified at the county level, standard errors are clustered by counties. Under the standard parallel trends assumption, the coefficients $\beta_{h\geq 0}$ estimate the impact of emigration on patenting activity carried by the relatives of the emigrant.

First, we report the estimates of (7) using a pre-post indicator for treatment status in Panel A of Table V. Emigration within the family is associated with an increase in patenting (column 1), which remains unchanged if we include county-by-year fixed effects (column 2) and is larger the more migrants from the family move to the United States (column 3). Since patenting is a skewed outcome, in column (4), we use a binary indicator that confirms the results. Importantly, the patents granted to the relatives of those who migrate to the US become more textually similar to US patents (column 5). This provides further evidence pointing at information flows between migrants and their relatives in the UK. Finally, in column (6), using the text-based impact measure, we confirm that the increased patenting activity generated by within-family migration is not restricted to low-impact innovations. Figure VI–Panel VIa provides the associated event-study estimates. We find no evidence of statistically significant pre-treatment coefficients and a large increase in patenting, which builds up over the three years following the emigration of the family member.

We then distinguish between emigrants who return and those who do not. Emigrants could interact with their families upon returning, but they could also maintain ties while abroad. In Panel B, we restrict the treatment to emigrants who never return to the UK. The estimates confirm that even when emigrants do not return, they nonetheless promote innovation within their families in the UK. Comparing the coefficients in Panel A and B, we find that the treatment effect of non-return migrants is about 70% of the average treatment effect, irrespective of return status. This difference is consistent with the descriptive evidence discussed in section VI.A and confirms that migrants promote innovation in their origin communities even when they do not return.

VI.B.2 Transatlantic Emigration Within Neighborhoods

Geographical proximity between the origin of emigrants and stayers is an alternative proxy for local social networks. In this section, we show an increase in the innovation activity of stayers whose former neighbors migrated to the US.

We leverage the granular nature of our data and perform an individual-level analysis. First, we extract all men aged between 18 and 50 in 1900 that do *not* emigrate from the 1891 census. We create a yearly balanced panel that reports the number of patents obtained by each individual between 1880 and 1900 using the linked inventor-census data described in Appendix A.II.7. We complement this data with information on the geographical proximity between these stayers and migrants to the US. Specifically, we define a variable $D_{p,t}$ that codes the periods since at least one individual living within k kilometers from non-migrant p migrates to the US and zero otherwise. In the baseline analysis, we consider a threshold k of five kilometers.[28]

The regression specification mirrors (7), except that the variable $D_{p,t}$ substitutes $D_{f,t}$. All regressions include individual and year-fixed effects, and in various specifications, we include district-by-time and parish-by-time fixed effects to control for time-varying heterogeneity at fine levels of spatial aggregation. Standard errors are clustered at the parish level because neighborhoods form subdivisions of parishes.

Table VI (Panel A) reports the results. Within-neighborhood migration to the United States has a positive and statistically significant impact on the innovation activity of stayers (column 1). Importantly, the effect remains when including parish-by-time fixed effects (column 3). In this case, the identifying variation consists of within-parish neighborhood-level emigration and ensures that we compare similar areas. In column (4), we show that conditional on having at least one emigrant in

[28] In Figure C.7, we show that the results are robust to alternative thresholds. In particular, the estimated treatment effect remains positive as in the baseline specification. Exceedingly restrictive thresholds, however, exclude a large number of treated individuals, and consequently, the estimated treatment effect is biased toward zero. Slack definitions of neighborhoods, by contrast, introduce measurement error, which reduces the precision of the estimates. We discuss these modeling choices in Appendix C.III.

the neighborhood, having more does not scale up the positive effect of emigration on innovation. In column (5), we use a binary indicator instead of the (log) number of patents, which confirms the baseline results. Importantly, in column (6), we find that those who are exposed to US emigrants through neighborhood ties produce patents that are more similar to those issued in the United States. This pattern confirms that neighborhood migrants plausibly transfer knowledge to their communities of origin. As in the rest of the paper, column (7) shows that neighborhood out-migration also promotes high-impact patenting. Figure VIb replicates these estimates in an event-study framework. We do not find statistically significant pre-treatment coefficients, even though these are not precisely estimated. The effect of neighborhood out-migration is largest four to five years after the treatment is first active and decreases thereafter.

In analogy to the family analysis, in Panel B, we restrict the attention to non-return migrants. The framework mirrors the previous specification, except that we now only include non-return migrants in the definition of the treatment $D_{f,t}$. We find that emigration within the neighborhood increases innovation even if the emigrant never comes back to the United Kingdom. In this case, the estimates in Panels A and B are largely overlapping; hence, the contribution of return migrants appears modest.

In Figure B.2, we estimate the baseline regression and interact the treatment variable with dummies for occupational categories of the inventor. We find substantial heterogeneity in response to neighborhood out-migration: treatment effects are larger for positively selected inventors working as entrepreneurs, utility workers—a catch-all term which comprises independent inventors—, chemistry and metallurgy workers, and engineers. By contrast, inventors employed in low-skilled occupations, such as agriculture and construction, do not react to exposure to within-neighborhood out-migration.

Taken together, the results presented in this section highlight the importance of social networks in driving the return innovation. As evidenced by the text-based measure of similarity between British and US patents, emigrants generate knowledge flows that benefit those communities. Importantly, these effects operate even in the absence of physical return migration.

VI.C Information Technologies and Knowledge Flows

Next, we explore how migration ties interacted with information technologies to foster the flow of novel knowledge from the United States to the United Kingdom. We focus on the main information technology of the period: the telegraph.

The first transatlantic telegraphic cable connected the US and UK domestic networks in 1866. The telegraph represented a major revolution in communication technology that drove unprecedented market integration (Steinwender, 2018). Before 1866, steam mail was the cheapest and fastest way to communicate between the UK and the US. It took seven to fifteen days to transmit information in this way. This delay was reduced to one day overnight between June 27 and 28, 1866. The connection timing was unanticipated and exogenous (Steinwender, 2018).[29]

Our hypothesis is that the telegraph represented a shock to information frictions across the ocean, facilitating the exchange of knowledge between emigrants and their communities of origin. The telegraph could also operate *indirectly* by facilitating the market integration between the US and the UK, thus further fostering knowledge flows (Aleksynska and Peri, 2014). To test these hypotheses, we estimate the following difference-in-differences models:

$$y_{i,t} = \alpha_i + \alpha_t + \sum_{h=-a}^{b} \beta_h \times [\text{US Emigrants}_i \times I(t-1866=h)] + \varepsilon_{i,t}, \tag{8a}$$

$$y_{ik,t} = \alpha_{ik} + \alpha_{it} + \alpha_{kt} + \sum_{h=-a}^{b} \beta_h \times [\text{Knowledge Exposure}_{ik} \times I(t-1866=h)] + \varepsilon_{ik,t}, \tag{8b}$$

where i, k, and t denote a district, technology class, and year, respectively. The terms (US Emigrants$_i$) and (Knowledge Exposure$_{ik}$) denote the number of US emigrants and exposure to US knowledge in the 1870s.[30] Finally, the term $I(t-1866=h)$ denotes the number of years since the transatlantic cable was laid down. In equation (8a), the treatment coefficients $\{\beta_{h\geq 0}\}$ quantify the effect of the transatlantic cable by comparing districts by the number of US emigrants; in equation (8b), we also leverage variation across sectors and exposure to US innovation.

We report the static versions that combine pre- and post-treatment years into two periods in column (1) of Table VII. Panel A reports the estimates of equation (8a), while Panel B refers to (8b). We estimate a positive and significant effect of the transatlantic telegraph on innovation. To provide more convincing evidence on the plausibility of this result, we test if the transatlantic cable affects innovation only in districts connected to the British domestic network.[31] We thus reconstruct the entire telegraph network before the introduction of the transatlantic cable. The exact location of each station is displayed in Appendix Figure A.1. In columns (3) and (4), we show that the positive effect

[29] The project for a transatlantic telegraphic cable had been underway for a long time before 1866. Previous attempts in 1857, 1858, and 1865 all failed due to logistic and technical challenges. The 1866 attempt was thus one among many, and its success had not been anticipated.

[30] The cable was laid down in 1866. Our migration data started in 1870. To construct district-level emigration, we can only use emigrants from 1870–1875. This would be problematic if the telegraph fostered out-migration, which, by available historical accounts, was not the case.

[31] We do not claim that there were no cross-district spillover effects even if districts were not connected to the domestic UK network. We nonetheless believe the effect on connected districts would arguably be more significant.

of the telegraph is exclusively driven by districts connected to the domestic UK network. We fail to detect any significant effect on non-connected districts. In column (5), we document that British patents became more similar to US patents after the telegraph connected the two countries. The quantitative effects are modest: moving from the 25th to the 75th percentile of US emigration yields a 2.9% increase in the number of patents produced after 1866. In connected districts, the magnitude amounts to a 3.6% increase. The same shift increases the similarity of British and American patents by approximately 7%.

Because the location of telegraph stations was not random, one may argue that this exercise only reflects pre-existing differences between connected and non-connected districts. Identification in this setting requires that patenting in connected and unconnected districts was on the same trend before the introduction of the telegraph and that it would not have differed had the cable not been laid down. In Figure VII, we report dynamic double-differences estimates of equation (8b), which we estimate separately on connected and unconnected districts. We find that connected and unconnected districts were on the same trend before 1866. We estimate positive and significant treatment effects only for the former and after 1866, whereas the patenting in the latter does not respond to the shock. In 1873 and 1874, the second and third cables became operational.

VI.D Migration Networks and Information Flows Beyond Innovation: The Coverage of American News in British Newspapers

Until this point, we have restricted the focus of the analysis to information flows related to new technologies. In this section, we document that migration ties between the UK and the US generated general-purpose information flows beyond those directly related to innovation.

We rely on the British Newspaper Archive, which contains the digitized contents of thousands of historical British newspapers (for a discussion of the dataset, see Beach and Hanlon, 2023). To proxy for information flows between the US and the UK, we construct a measure of coverage of US-related information flows in UK newspapers by counting the references to US-related words.

We estimate three sets of regression equations:

$$\text{US Mentions}_{i,t} = \alpha_i + \alpha_t + \beta_1 \times \text{US Emigrants}_{i,t} + \varepsilon_{i,t}, \tag{9a}$$

$$\text{US State Mentions}_{is,t} = \alpha_{is} + \alpha_t + \beta_2 \times \text{US Emigrants}_{i\to s,t} + \varepsilon_{is,t}, \tag{9b}$$

$$\text{US County Mentions}_{ij,t} = \alpha_{ij} + \alpha_t + \beta_3 \times \text{US Emigrants}_{i\to j,t} + \varepsilon_{ij,t}, \tag{9c}$$

where i, j, s, and t denote a UK district, a US county, a US state, and a decade, respectively.

Regression (9a) is run at the district level and leverages variation in the number of emigrants to the United States; in regressions (9b) (resp. (9c)), instead, we look at district-by-state (resp. district-by-county) migration flows.

Table VIII reports the results. Columns (1–3), (4–5), and (7–8), respectively display the estimated β_i coefficients of estimated equations (9a), (9b), and (9c). Columns (1), (4), and (7) report the effect on the log(1+) number of mentions of "United States," single states, and single counties. In columns (2), (5), and (8), we exclude from the sample all districts where no single newspaper is based in the sample period. Columns (3), (6), and (9) display the association between emigration and the number of US-related topics normalized by (1+) the number of active newspapers in the district. Appendix Table C.14 shows that the associated estimates obtained using the instrumental variables described in Section C.I.4 are consistent with the OLS estimates.

We find a positive effect of out-migration on newspaper coverage of general-interest US-related news. We interpret this pattern as evidence that out-migration generates information flows between the areas where emigrants settle and where they originate. We cannot disentangle—-and this goes beyond the scope of this paper—the precise underlying mechanism. For example, increased coverage of US-related news may be demand-driven because the local population may demand information covering the areas where their relatives settled. On the other hand, US emigrants could have sponsored local newspapers to cover news about the areas where they were located. In this sense, our estimates may reflect a supply-side factor. Taken together, these results show that out-migration fostered cross-country information flows.

VI.E Alternative Mechanisms

To conclude this section, we discuss additional mechanisms that may explain the return innovation result, which we cannot directly test in the paper.

Temporary Migrations In our study of the mechanisms behind the return innovation effect, we concluded that physical return is an important determinant but not the exclusive driver. It is possible, however, that short-term temporary migrations influence the dynamics of innovation in the UK. Since we construct migration flows from population censuses, which are conducted every ten years, our data cannot identify temporary migrants. For the same reasons, we cannot quantify the importance of industrial espionage.

However, we believe that the quantitative effects of temporary migrations and industrial espionage are modest. First, the notion of a "temporary migrant" in XIX-century transatlantic migration is not well-defined. Piore (1980) refers to Southern and Eastern European migrants as temporary because they planned to return to their origin countries at some point. This spell could take, however, decades. For example, a one-way cabin travel ticket from New York to Liverpool, at roughly 100$, would cost as much as 20% of the average annual US income. The extent of short-term stays must have been, therefore, relatively limited. Moreover, Piore (1980) notes that "temporary" migrants were relatively low-skilled and, therefore, less likely to operate technology transfer. Industrial espionage does not appear to be quantitatively sufficient to generate the return innovation effect that we estimate. Finally, our research designs speak against the temporary migration and the industrial espionage mechanisms. For temporary migration or industrial espionage to explain the double and triple differences result, in fact, one would need such flows to be correlated with the county-level innovation shocks. This channel seems unlikely, although it cannot be directly tested and refuted due to the absence of data.

Monetary Remittances Along with classical "brain drain" arguments, monetary remittances have been a major subject of investigation in the literature. While the contribution of remittances to economic development appears to be modest, it is possible that this inflow of capital may have sustained increased innovation, perhaps by relaxing constraints in access to credit (Gorodnichenko and Schnitzer, 2013). This capital inflow, however, could explain why out-migration influences the direction of innovation unless knowledge *and* monetary remittances go hand in hand. Disaggregated data on financial remittances, unfortunately, do not exist. Hence, this is a possibility that we cannot explore. It nonetheless highlights that, if anything, financial and "knowledge" remittances are likely to shape innovation in a complementary way rather than in a mutually exclusive one.

VII Conclusions

Previous literature has shown that the diffusion of innovation across countries is a major driver of long-run growth and economic convergence. However, evidence on *how* innovation diffuses across countries remains limited. In this paper, we provide the first causal evidence that out-migration enables the diffusion of innovation from the country of destination toward the country of origin of migrants.

Our analysis focuses on the English and Welsh mass migration to the United States between 1870 and 1940. We link the individual-level census records of British immigrants in the US to the UK population census to measure spatially disaggregated emigration flows. We complement these data with newly digitized patents that, added to existing data, allow us to cover the universe of patents granted in England and Wales in the nineteenth and twentieth centuries. The absence of stringent international intellectual property protection allows us to use patents as a measure of the diffusion of knowledge across countries.

Using a double and triple differences research design, we document that exposure to foreign technology through migration ties contributes to its diffusion in the country of origin of migrants. First, we document that the volume of innovation in the UK increases in response to higher exposure to US innovation through emigration. Second, innovation activity in the UK shifts towards technologies that emigrants are most exposed to in the US. By looking at the textual similarity between UK and US patents, we find that exposure to US knowledge stimulates technology transfer. Additionally, we show that this diffusion involves both low and high-impact UK innovations. We define this phenomenon "return innovation."

We then turn to studying the drivers of return innovation. The physical return of migrants explains approximately half of the effect. However, we find that interactions between emigrants and their communities of origin represent another important channel of technology diffusion, even in the absence of return migration. This is further supported by the fact that information technologies, such as the telegraph, facilitated knowledge flows between emigrants' destination areas in the US and their region of origin in the UK.

While the setting of this paper is historical, our results are likely to have implications in contemporaneous settings. In fact, our findings echo qualitative evidence by Saxenian (1999, 2006), who documents similar return innovation effects in the Taiwanese and Indian emigration to the Silicon Valley area at the end of the 20th century. Taken together, our results document that emigration does not necessarily lead to underdevelopment or stagnation, as suggested by the "brain drain" hypothesis (Docquier and Rapoport, 2012), but it can foster the diffusion of innovation, which is a leading driver of economic growth. The return innovation and brain drain effects are likely to coexist, and which prevails is likely to be a function of the type of migration (skilled or unskilled), as well as the relative position of the origin and destination countries in the technology frontier. Beyond the relative size of these two effects, our results suggest that fostering economic integration between the country of origin of migrants and their country of emigration is likely to promote knowledge exchange, including return innovation.

Finally, given the recent advances in information and communication technologies, a natural question is whether emigrants' physical exposure to foreign technology is still necessary to promote the diffusion of innovation. While we cannot speak directly to the substitutability of in-person interactions, the existing literature shows that physical proximity is still a major driver of the production and diffusion of knowledge.[32]

[32] Among others, Akcigit *et al.* (2018) highlight the importance of interactions in shaping the career trajectories of inventors. Prato (2022) shows that immigrant inventors retain ties with their colleagues in their origin countries, fostering technology transfer and productivity. Boudreau, Brady, Ganguli, Gaule, Guinan, Hollenberg and Lakhani (2017) document that

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Tables

Table I. Descriptive Statistics

	Mean	Std. Dev.	Min	Max	Units	Obs.
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Demographics (in 1880)						
Population$_i$ (1,000s)	39.988	46.183	0.184	310.706	621	621
Share of Men$_i$ (%)	49.238	2.124	38.662	56.616	621	621
Share of Employment$_i$ (%)	61.091	7.240	0.000	74.427	621	621
in Agriculture$_i$ (%)	14.406	6.892	1.989	31.117	621	621
in Construction$_i$ (%)	3.747	1.597	1.420	20.618	621	621
in Engineering$_i$ (%)	3.818	1.483	0.848	11.843	621	621
in Public and Liberal Occupations$_i$ (%)	2.573	1.674	0.819	16.045	621	621
in Other Manufacturing$_i$ (%)	3.289	2.772	0.618	19.684	621	621
in Textiles$_i$ (%)	4.996	5.135	0.736	34.390	621	621
in Trade$_i$ (%)	1.612	1.003	0.372	9.783	621	621
in Transportation$_i$ (%)	2.382	1.340	0.438	13.857	621	621
Panel B. Emigration to the United States						
US Emigrants$_{id}$	105.783	148.023	0.000	1752.157	621	3726
Return US Emigrants$_{id}$	11.845	17.108	0.000	185.591	621	2484
Panel C. Patents						
Total Patents$_{it}$	21.355	68.158	0.000	2088.000	621	31671
Patents by Technology Class:						
in Electricity$_{it}$	1.855	14.724	0.000	1084.000	621	31671
in Instruments$_{it}$	1.777	7.349	0.000	217.000	621	31671
in Lighting and Heating$_{it}$	1.486	5.487	0.000	145.000	621	31671
in Personal Goods$_{it}$	1.810	6.573	0.000	170.000	621	31671
in Transportation$_{it}$	3.499	10.761	0.000	244.000	621	31671
Panel D. Linked Inventor-Census Sample						
Number of Patents$_{it}$	0.121	0.842	0.000	274.000	110532	2210640
Age$_i$	37.104	13.729	9.000	79.000	110532	110532
Employed in:						
Agriculture$_i$	0.133	0.339	0.000	1.000	110532	110532
Construction$_i$	0.140	0.347	0.000	1.000	110532	110532
Engineering$_i$	0.164	0.371	0.000	1.000	110532	110532
Trade$_i$	0.089	0.285	0.000	1.000	110532	110532
Transportation$_i$	0.092	0.289	0.000	1.000	110532	110532
Neighborhood Emigrants$_i$	2.295	4.081	0.000	53.424	110532	110532
Non-Return Neighborhood Emigrants$_i$	2.257	4.012	0.000	52.677	110532	110532

Notes. This Table lists descriptive statistics for the variables used in the main analysis at the district (Panel A), district-decade (Panel B), district-year (Panel C), and individual level (Panel D). Demographic data in Panels A and D are tabulated from the population census. Panel A refers to the 1880 census. Emigration data in Panels A and D are computed from the linked migrant sample. Demographic data are cross-walked to consistent 1891 district borders. The subscripts report the aggregation level: Panel A by district i; Panel B by district-decade id; Panel C by district-year it; Panel D by individuals i. Referenced on page(s) 11, 13.

Table II. Exposure to Innovation in the United States and the Volume and Direction of Innovation in the United Kingdom

	Patents by District				Patents by District-Technology			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Number	Number	US Patents Similarity	High Impact	Number	Number	US Patents Similarity	High Impact
Dependent Variable Mean	*3.518*	*3.518*	*162.555*	*2.042*	*1.006*	*1.006*	*74.488*	*0.388*
US Emigrants (1,000s)	0.882***	0.488**	24.081***	1.204***				
	(0.185)	(0.222)	(7.067)	(0.221)				
Knowledge Exposure					0.023***	0.006***	0.231***	0.022***
					(0.002)	(0.001)	(0.058)	(0.001)
District FE	Yes	Yes	Yes	Yes	–	–	–	–
Decade FE	Yes	–	Yes	Yes	–	–	–	–
Controls × Time	No	Yes	No	No	–	–	–	–
County-Year FE	No	Yes	No	No	–	–	–	–
District-Year FE	–	–	–	–	Yes	Yes	Yes	Yes
Technology FE	–	–	–	–	Yes	–	Yes	Yes
District-Technology FE	–	–	–	–	No	Yes	No	No
Technology-Year FE	–	–	–	–	No	Yes	No	No
Number of Districts	621	620	621	621	621	621	621	621
Observations	3,726	3,720	3,726	3,726	70,433	70,433	70,433	70,433
Std. Beta Coef.	0.065	0.036	0.037	0.097	0.185	0.050	0.024	0.292

Notes. This Table reports the association between emigration to the United States and innovation in the United Kingdom. In columns (1–4) (resp. 5–8), the unit of observation is a district (resp. district-technology pair) observed at a decade frequency between 1870 and 1930. In columns (1–2) and (5–6), the dependent variable is the log(1+) number of patents. In columns (3) and (7), the dependent variable is the average text-based similarity between UK and US patents issued in the previous five years. In columns (4) and (8), the dependent variable is the log(1+) of the number of patents in the top 20% of the impact distribution ("Breakthrough" patents). In columns (1–4), "US Emigrants (1,000s)" is the number of migrants to the United States from the given district and decade, in thousands. In columns (5–8), "Knowledge Exposure" is defined in equation (1). Columns (1) and (3–4) include district and decade fixed effects. Column (2) includes district fixed effects, district-level controls measured in 1880 and interacted with decade indicators, and county-by-decade fixed effects. Columns (5) and (7–8), include district-by-year and technology fixed effects. Column (6) includes district-by-year, district-by-technology, and technology-by-year fixed effects. Standard errors, reported in parentheses, are clustered at the district level. Referenced on page(s) 20, 21. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$

TABLE III. The Effect of Shocks to Innovation in the United States on Innovation in the United Kingdom

	Patents by District			Patents by District-Technology		
	(1) Number	(2) US Patents Similarity	(3) High Impact	(4) Number	(5) US Patents Similarity	(6) High Impact
Dependent Variable Mean	*1.687*	*121.561*	*0.736*	*0.292*	*30.124*	*0.082*
Post × US Innovation Shock	0.091**	18.523***	0.082*	0.064***	8.760***	0.020***
	(0.045)	(3.473)	(0.043)	(0.009)	(1.145)	(0.006)
District FE	Yes	Yes	Yes	–	–	–
Year FE	Yes	Yes	Yes	–	–	–
District-Year FE	–	–	–	Yes	Yes	Yes
Technology-Year FE	–	–	–	Yes	Yes	Yes
District-Technology FE	–	–	–	Yes	Yes	Yes
Number of Districts	621	621	621	621	621	621
Observations	31,671	31,671	31,671	601,749	601,749	601,749

Notes. This Table reports the effect of shocks to US innovation activity on innovation in the United Kingdom. In columns (1–3), the unit of observation is a district observed at a yearly frequency between 1870 and 1930. In columns (4–6), the unit of observation is a district-technology pair observed over the same period. In columns (1) and (4), the dependent variable is the log(1+) number of patents. In columns (2) and (5), the dependent variable is the average text-based similarity between UK patents and US patents issued in the previous five years. In columns (3) and (6), the dependent variable is the log(1+) number of patents in the top 20% of the impact distribution ("Breakthrough" patents). "Post" is an indicator equal to one for all years after the observation unit is exposed to a shock to US innovation activity, equal to zero otherwise. "US Innovation Shock" is defined in Section IV.D. Columns (1–3) include district and year fixed effects. Columns (4–6) include district-by-year, technology-by-year, and district-by-technology fixed effects. Standard errors, reported in parentheses, are clustered by district. Referenced on page(s) 22. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$

TABLE IV. Return Migration and Innovation in the United Kingdom

	Patents by District			Patents by District-Technology		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable Mean	*3.553*	*3.898*	*3.738*	*1.011*	*1.170*	*1.090*
US Emigrants$_t$ (1,000s)	0.540***		-0.101			
	(0.161)		(0.284)			
US Emigrants$_{t-1}$ (1,000s)		0.735***	0.479***			
		(0.157)	(0.167)			
Return US Emigrants$_t$ (1,000s)	4.050***		2.723			
	(1.394)		(1.915)			
Return US Emigrants$_{t-1}$ (1,000s)		0.495	2.623			
		(1.177)	(2.057)			
Knowledge Exposure$_t$				0.012**		0.026**
				(0.005)		(0.012)
Knowledge Exposure$_{t-1}$					0.012***	0.003
					(0.004)	(0.003)
Return Knowledge Exposure$_t$				0.671***		0.043
				(0.216)		(0.191)
Return Knowledge Exposure$_{t-1}$					0.594*	-0.390
					(0.285)	(0.471)
District FE	Yes	Yes	Yes	–	–	–
Decade FE	Yes	Yes	Yes	–	–	–
District-Year FE	–	–	–	Yes	Yes	Yes
Technology FE	–	–	–	Yes	Yes	Yes
Number of Districts	621	621	621	621	621	621
Observations	2,484	2,484	1,863	47,196	47,196	35,397

Notes. This Table compares the effect of out-migration and return-migration on innovation in the UK. The unit of observation is a district (columns 1–3) and a district-technology (columns 4–6). Units are observed at decade frequency between 1880 and 1910 (columns 1–2 and 4–5) and between 1880 and 1900 (columns 3 and 6). Different sample periods depend on the lag structure. In all columns, the dependent variable is the log(1+) number of patents. "US Emigrants (1,000)" is the number of emigrants to the US in the current decade or in the previous one ($t-1$), in thousands. "Return US Emigrants (1,000s)" is the number of emigrants to the US who return to the UK in the current decade or in the previous one ($t-1$), in thousands. "Knowledge Exposure" is constructed following equation (1) and refers to the current decade or the previous one ($t-1$). "Return Knowledge Exposure" is defined similarly to Knowledge Exposure, but only look at flows of emigrants who eventually return to the UK. Columns (1–3) include district and decade-fixed effects. Columns (4–6) include district-by-time and technology-fixed effects. Standard errors, reported in parentheses, are clustered by district. Referenced on page(s) 27. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$

TABLE V. Within-Family Migration to the United States and Innovation in the United Kingdom

	Number of Patents				Text-Based Measures	
	(1)	(2)	(3)	(4)	(5)	(6)
	Number	Number	Number	I(Patents > 0)	US Patents Similarity	High Impact
Panel A. Family Emigration						
Dependent Variable Mean	*4.919*	*4.919*	*4.919*	*5.835*	*6.612*	*1.229*
US Emigrant in Family × Post	1.375***	1.505***	-0.312	1.303***	3.873***	0.452***
	(0.363)	(0.314)	(0.218)	(0.402)	(0.567)	(0.118)
US Emigrant in Family × Post × N. of Emigrants			1.299***			
			(0.316)			
Number of Families	46,864	46,864	46,864	46,864	46,864	46,864
Observations	2,858,704	2,858,704	2,858,704	2,858,704	2,858,704	2,858,704
Panel B. Family Non-Return Emigration						
Dependent Variable Mean	*4.919*	*4.919*	*4.919*	*5.835*	*6.612*	*1.229*
Non-Return US Emigrant in Family × Post	1.030***	1.152***	-1.181**	0.970**	3.065***	0.306***
	(0.333)	(0.281)	(0.448)	(0.373)	(0.497)	(0.092)
Non-Return US Emigrant in Family × Post × N. of Emigrants			1.813***			
			(0.626)			
Number of Families	44,879	44,879	44,879	44,879	44,879	44,879
Observations	2,737,619	2,737,619	2,737,619	2,737,619	2,737,619	2,737,619
Family FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	–	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes. This Table reports the impact of emigrants to the United States on the innovation activity of their relatives who remain in the UK. The unit of observation is a family defined by all individuals with the same surname in the same county. Units are observed at yearly frequency between 1870 and 1930. In columns (1–3), the dependent variable is the log(1+) number of patents issued to family members in the UK. In column (4), the dependent variable is an indicator equal to one if family members in the UK were issued at least one patent, equal to zero otherwise. In column (5), the dependent variable is the average text-based similarity between UK patents and US patents issued in the previous five years. In column (6), the dependent variable is the log(1+) number of patents in the top 20% impact distribution ("Breakthrough" patents). "US Emigrant in Family × Post" is an indicator equal to one in the year the first emigrant in the family moves to the US and in later years, and equal to zero in the previous years. "US Emigrant in Family × Post × N. of Emigrants" is an interaction between "US Emigrant in Family × Post" and the number of emigrants from that family. "Non-Return US Emigrant in Family × Post" is an indicator equal to one in the year the first emigrant in the family moves to the US (without returning to the UK) and in later years and equal to zero in the previous years. "Non-Return US Emigrant in Family × Post × N. of Emigrants" is an interaction between "Non-Return US Emigrant in Family × Post" and the number of non-return emigrants from that family. All columns include family (i.e., surname-county) and year fixed effects. Column (3) also includes county-by-year fixed effects. Standard errors, reported in parentheses, are clustered at the county level. The dependent variables in columns (1–4) are multiplied by 100. Referenced on page(s) 28. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$

TABLE VI. Within-Neighbohood Emigration to the United States and Innovation in the United Kingdom

	Number of Patents					Text-Based Measures	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Number	Number	Number	Number	I(Patents > 0)	US Patents Similarity	High Impact
Panel A. Neighborhood Emigration							
Dependent Variable Mean	*6.721*	*6.721*	*6.741*	*6.775*	*8.483*	*6.792*	*1.550*
Post × Emigrant in Neighborhood	0.440***	0.236**	0.254**	0.205	0.552***	0.477***	0.116**
	(0.130)	(0.110)	(0.116)	(0.154)	(0.160)	(0.132)	(0.052)
Post × N. Emigrants in Neighborhood				0.210			
				(0.209)			
Number of Individuals	136,880	136,872	134,936	117,649	136,880	136,880	136,880
Observations	2,737,600	2,737,440	2,698,720	2,352,980	2,737,600	2,737,600	2,737,600
Panel B. Neighborhood Non-Return Emigration							
Dependent Variable Mean	*6.721*	*6.721*	*6.741*	*6.775*	*8.483*	*6.792*	*1.550*
Post × Non-Return Emigrant in Neighborhood	0.409***	0.252**	0.263**	0.430***	0.517***	0.453***	0.109**
	(0.130)	(0.113)	(0.120)	(0.163)	(0.159)	(0.133)	(0.054)
Post × N. Non-Return Emigrants in Neighborhood				0.064			
				(0.216)			
Number of Individuals	120,575	120,567	118,628	102,714	120,575	120,575	120,575
Observations	2,411,500	2,411,340	2,372,560	2,054,280	2,411,500	2,411,500	2,411,500
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Parish-Year FE	No	No	Yes	No	No	No	No
District-Year FE	No	Yes	–	No	No	No	No
Year FE	Yes	–	–	Yes	Yes	Yes	Yes

Notes. This Table reports the impact of emigrants to the United States on the innovation activity of their former neighbors in the United Kingdom. The unit of observation is an individual inventor observed yearly between 1880 and 1900. The sample includes the universe of British inventors linked to the 1891 population census, as detailed in the main text. In columns (1–4), the dependent variable is the log(1+) number of patents granted to members of the emigrant's family. In column (5), the dependent variable is an indicator equal to one if members of the emigrant's family are granted at least one patent, equal to zero otherwise. In column (6), the dependent variable is the average text-based similarity between UK patents and US patents issued in the previous five years. In column (7), the dependent variable is the log(1+) number of patents in the top 20% of the impact distribution. "Post × Emigrant in Neighborhood" is an indicator equal to one in the year the first neighbor of the inventor move to the US and in subsequent years, and equal to zero in the previous years. "Post × N. Emigrants in Neighborhood" is an interaction between "Post × Emigrant in Neighborhood" and the number of emigrants to the US from the neighborhood. "Post × Non-Return Emigrant in Neighborhood" is an indicator equal to one in the year the first neighbor of the inventor move to the US (without returning to the UK) and in subsequent years and equal to zero in the previous years. "Post × N. Non-Return Emigrants in Neighborhood" is an interaction between "Post × Non-Return Emigrant in Neighborhood" and the number of emigrants to the US from the neighborhood. Columns (1) and (4–7) include inventor and year fixed effects. Column (2) includes inventor and district-by-year fixed effects. Column (3) includes inventor and parish-by-year fixed effects. Standard errors, reported in parentheses, are clustered at the parish level. The dependent variables in columns (1–4) are multiplied by 100. Referenced on page(s) 29. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$

TABLE VII. The Transatlantic Telegraph Cable and Innovation in the United Kingdom

	Number of Patents				Text-Based Measures	
	(1) Number	(2) Number	(3) With Station	(4) Without Station	(5) US Patents Similarity	(6) High Impact
Panel A. Patents by District						
Dependent Variable Mean	*0.803*	*0.803*	*0.914*	*0.546*	*21.026*	*0.311*
Post Telegraph × US Emigrants	0.617***	0.116	0.698***	-0.327	148.198***	0.769***
	(0.201)	(0.266)	(0.237)	(0.328)	(10.637)	(0.160)
Post Telegraph × US Emigrants × N. Stations		0.215**				
		(0.086)				
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Districts	621	621	435	186	621	621
Observations	16,146	16,146	11,310	4,836	16,146	16,146
Panel B. Patents by District-Technology						
Dependent Variable Mean	*0.091*	*0.091*	*0.099*	*0.070*	*3.090*	*0.022*
Post Telegraph × Knowledge Exposure	0.375***	0.195*	0.454***	0.037	59.277***	0.157***
	(0.080)	(0.104)	(0.093)	(0.166)	(4.594)	(0.041)
Post Telegraph × Knowledge Exposure × N. Stations		0.077***				
		(0.023)				
District-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
District-Technology FE	Yes	Yes	Yes	Yes	Yes	Yes
Technology-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Districts	621	621	435	186	621	621
Observations	306,774	306,774	214,890	91,884	306,774	306,774

Notes. This Table reports the effect of the transatlantic telegraph cable that connected the UK and the US in 1866 on innovation activity in the UK. In Panel A, the unit of observation unit is a district observed at yearly frequency between 1853 and 1879. In Panel B, the unit of observation is a district-technology class pair observed at a yearly frequency between 1853 and 1879. The analysis period starts in 1853 due to the availability of the patent data. We include years until 1879 to have a symmetric window around the first treatment period (1866). In columns (1–4), the dependent variable is the log(1+) number of patents. In column (5), the dependent variable is the average text-based similarity between UK and US patents issued in the previous five years. In column (6), the dependent variable is the log(1+) number of patents in the top 20% of the impact distribution. "Post Telegraph" is an indicator equal to one for years between 1866 and 1879, equal to zero otherwise. "US Emigrants" is the number of emigrants from the district to the US in the 1870s. "Knowledge Exposure", constructed following equation (1), refers to exposure to US innovation via out-migration in the 1870s. "N. Stations" is the number of telegraph stations located in the district. In column (3), we include districts with at least one telegraph station in 1862. In column (4), we exclude districts with one or more telegraph stations in 1862. In Panel A, all columns include district and time fixed effects. In Panel B, all columns include district-by-time, district-by-technology, and technology-by-time fixed effects. Standard errors, reported in parentheses, are clustered by district (in Panel A) and two-way by district and technology (in Panel B). Referenced on page(s) 31. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$

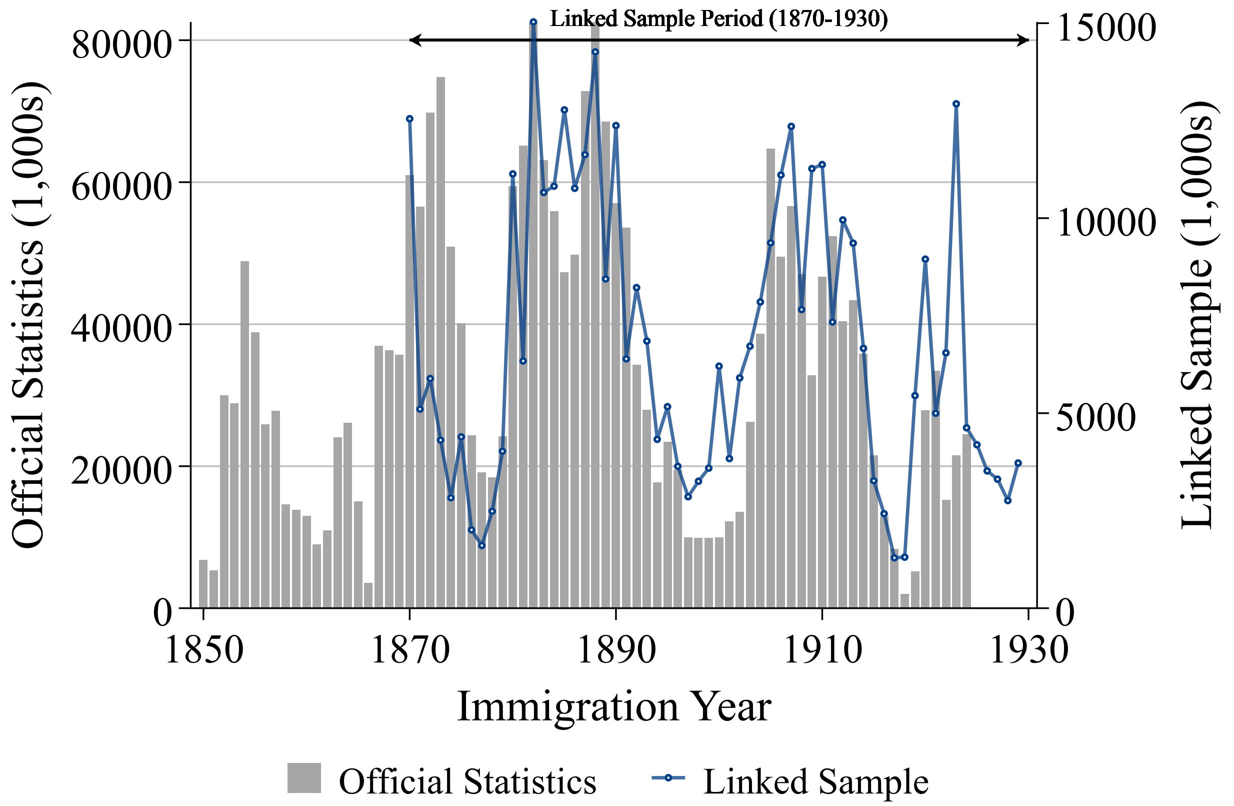
TABLE VIII. Emigration and Newspaper Coverage of US News

	Mentions of U.S.			Mentions of U.S. States			Mentions of U.S. Counties		
	(1) Total Mentions	(2) With Newspaper(s)	(3) Average Mentions	(4) Total Mentions	(5) With Newspaper(s)	(6) Average Mentions	(7) Total Mentions	(8) With Newspaper(s)	(9) Average Mentions
Dependent Variable Mean	*1.491*	*3.685*	*1.328*	*1.019*	*2.398*	*0.350*	*0.001*	*0.003*	*0.001*
US Emigrants (1,000s)	1.340***	0.654	0.936**	19.539***	10.024***	7.198***	6.710***	9.625***	3.216***
	(0.418)	(0.609)	(0.375)	(3.367)	(3.856)	(1.564)	(1.085)	(1.968)	(0.497)
UK District FE	Yes	Yes	Yes	–	–	–	–	–	–
UK District-US State FE	–	–	–	Yes	Yes	Yes	–	–	–
UK District-US County FE	–	–	–	–	–	–	Yes	Yes	Yes
Decade FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Districts	591	307	591	591	316	591	591	302	591
Observations	4,137	1,660	4,137	215,124	91,000	215,124	13,465,344	4,784,640	13,465,344
Std. Beta Coef.	0.071	0.045	0.056	0.042	0.024	0.038	0.014	0.015	0.011

Notes. This Table reports the association between emigration to the United States and newspaper coverage of US-related topics in the United Kingdom. The unit of observation is a district (columns 1–3), district-US state (columns 4–6), and district-US county (columns 7–9). Units are observed at a decade frequency between 1870 and 1930. The dependent variable is the log(1+) number of mentions of "United States" (1), of US states (4), and of US counties (7). In columns (2), (5), and (8), we exclude all districts where no newspaper is based at any point in time. In columns (3), (6), and (9), we use the average number of mentions per newspaper, computed as the ratio between the total number of mentions and the number of newspapers, as the dependent variable. "US Emigrants (1,000s)" is the number of US emigrants in thousands (columns 1–3), the number of emigrants, in thousands, between the district and the state (columns 4–6), and the number of emigrants, in thousands, between the district and the county (columns 7–9). All columns include dyadic fixed effects—i.e., district FEs in columns (1–3), district-by-state FEs in columns (4–6), and district-by-county FEs in columns (7–9)—as well as time fixed effects. Standard errors, reported in parentheses, are clustered at the district level. Referenced on page(s) 33. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$

Figures

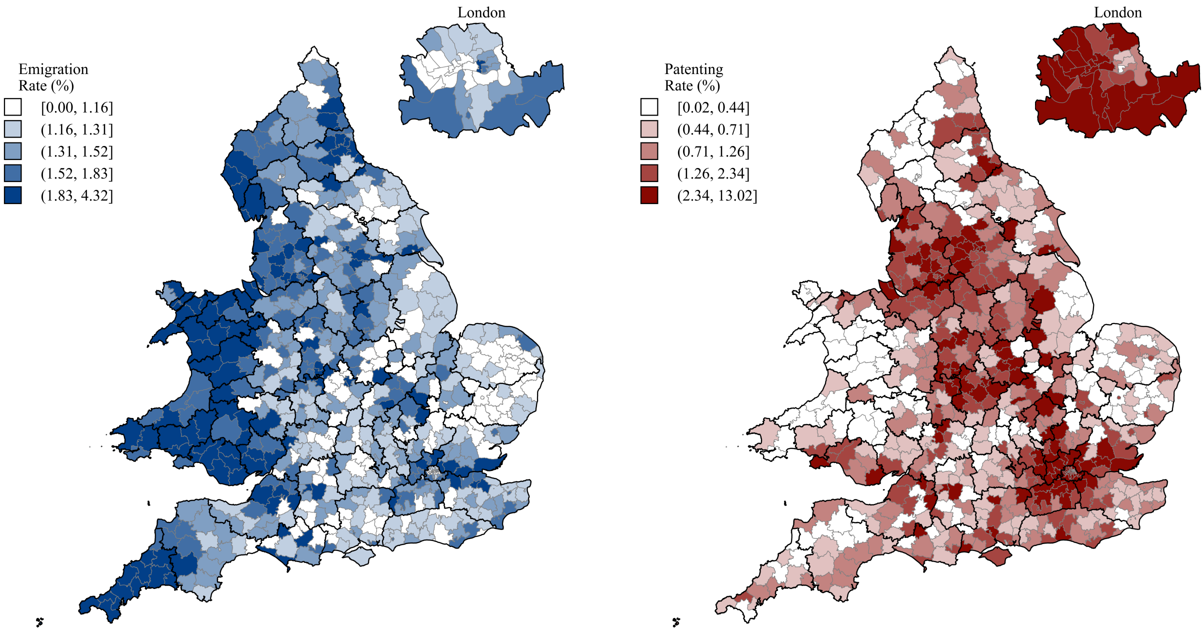
Figure I. British Emigration to the United States: Official Statistics and Linked Sample



Notes. This Figure compares the total number of English and Welsh immigrants in the United States as recorded in official statistics from Willcox (1928) with the linked emigrants' sample assembled in this paper. The gray bars report, on the left y-axis, the number of English and Welsh immigrants in the official statistics by their recorded immigration year in the United States. The blue line, whose values are reported on the right y-axis, reports the total number of English and Welsh immigrants in the US that appear in our matched sample. By construction, we can only match men who appear at least once in one British census. Numbers are in thousand units. The black two-sided arrow marks the period covered by the linked sample, i.e., the years between 1870 and 1930. Referenced on page(s) 11.

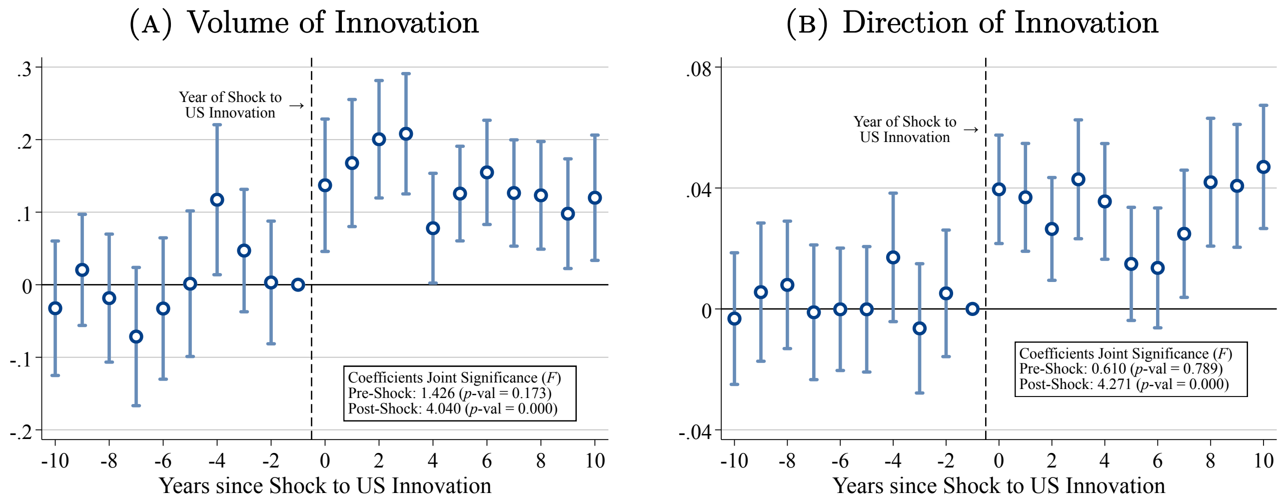
Figure II. Patenting and Emigration Rates in the United Kingdom

(a) Emigration Rate (%) (b) Patenting Rate (%)



Notes. This Figure reports the spatial distribution of emigrants across English and Welsh districts over the period 1870–1930 (Panel IIa) and the number of patents issued over the same period (Panel IIb). Both series are normalized by district population in 1891 and are reported in percentage points. Districts are displayed at 1891 historical borders, and the emigrant population is cross-walked to consistent borders. Lighter to darker tones of color indicate increasing quantiles of the variable. The London area is displayed separately. Referenced on page(s) 13.

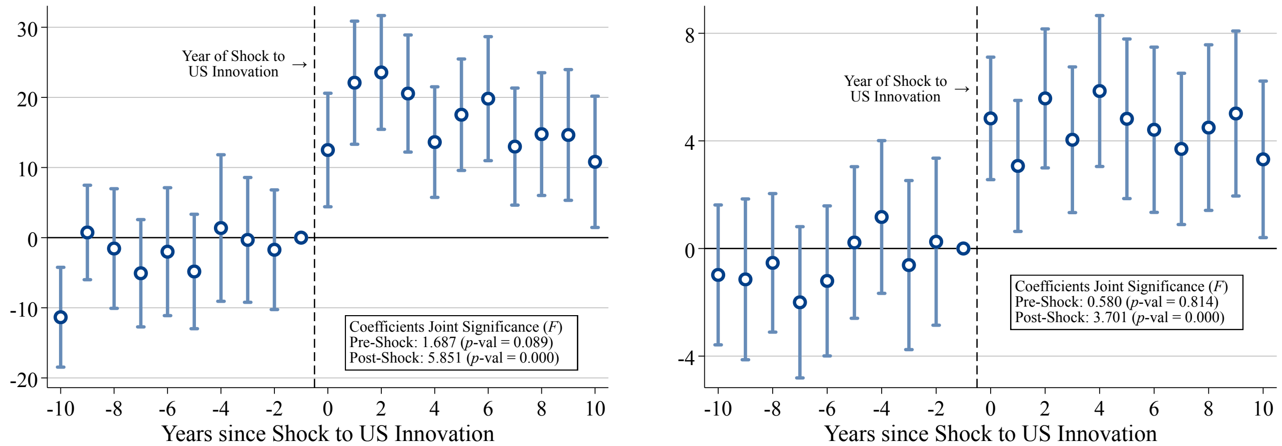
FIGURE III. Dynamic Effect of Exposure to Innovation Shocks in the United States



Notes. This Figure reports the impact of shocks to US innovation activity on innovation in the UK. In Panel IIIa, the unit of observation is a district observed at yearly frequency between 1870 and 1930; in Panel IIIb, the unit of observation is a district-technology pair observed over the same period. The dependent variable is the log(1+) number of patents. Each dot reports the coefficient of an indicator variable, which codes the time since the observation unit is exposed to a shock in US innovation activity through emigration ties. The black dashed line indicates the treatment period. The last period before the shock serves as the baseline category. In Panel IIIa, the regression includes district and year fixed effects; in Panel IIIb, the regression includes district-by-year, technology-by-year, and district-by-technology fixed effects. Standard errors are clustered at the district level. The bands report 95% confidence intervals. Each Figure reports separate F-statistics for the joint significance of the pre-and post-treatment coefficients and associated p-values. Referenced on page(s) 22.

Figure IV. Dynamic Effect of Exposure to Innovation Shocks in the United States on the Similarity Between British and American Patents

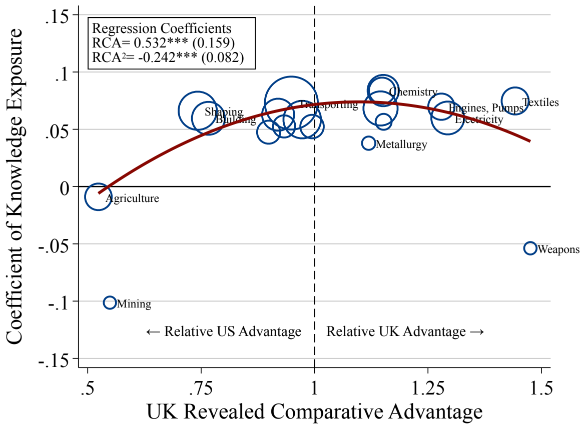
(A) Patents Pooled Across Technologies (B) Patents by Technology



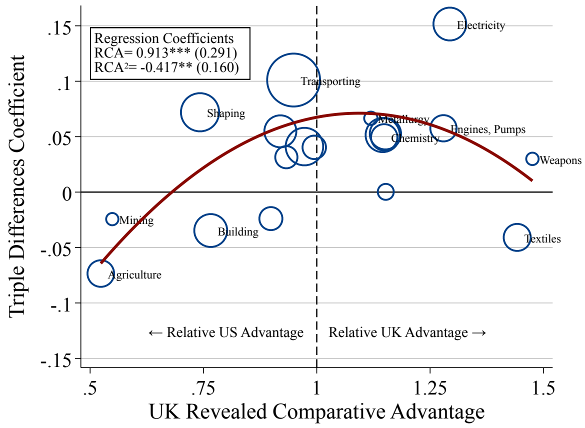
Notes. This Figure reports the impact of shocks to US innovation activity on innovation in the UK. In Panel IVa, the unit of observation is a district observed at yearly frequency between 1870 and 1930; in Panel IVb, the unit of observation is a district-technology pair observed over the same period. The dependent variable is the average text-based similarity of UK patents issued in a given period to US patents issued in the previous five years. Each dot reports the coefficient of an indicator variable, which codes the time since the observation unit is exposed to a shock in US innovation activity through emigration ties. The black dashed line indicates the treatment period. The last period before the shock serves as the baseline category. In Panel IVa, the regression includes district and year fixed effects; in Panel IVb, the regression includes district-by-year, technology-by-year, and district-by-technology fixed effects. Standard errors are clustered at the district level. The bands report 95% confidence intervals. Each Figure reports separate F-statistics for the joint significance of the pre-and post-treatment coefficients and associated p-values. Referenced on page(s) 23.

Figure V. Heterogeneous Effects of Exposure to Innovation in the United States Across Technologies

(a) Knowledge Exposure (OLS)

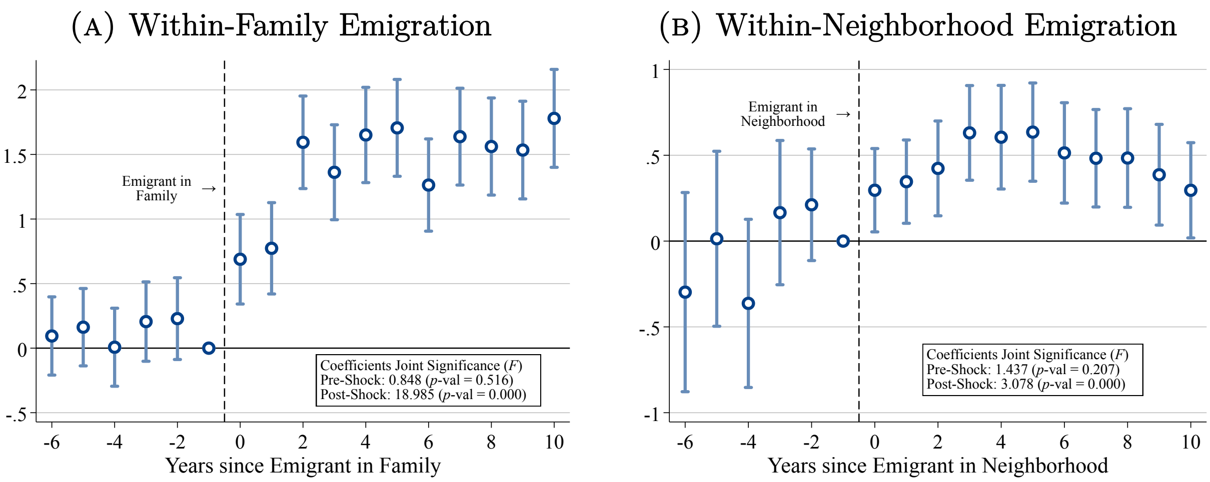


(b) Triple-Differences Estimates



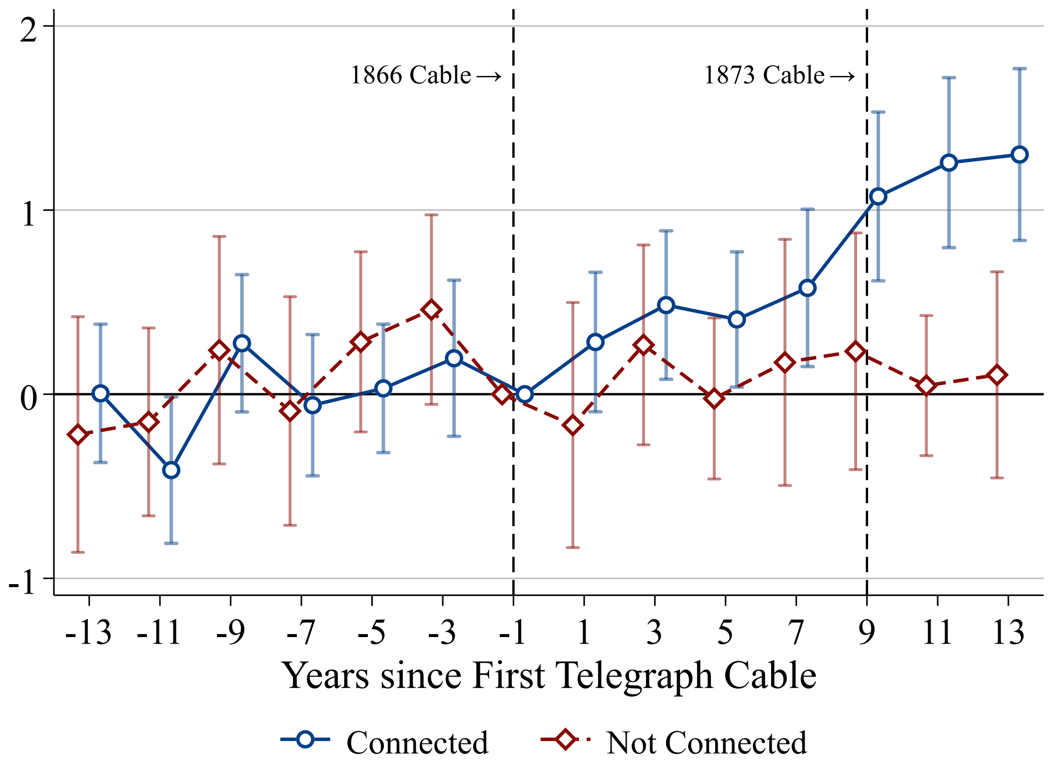
Notes. This Figure reports the heterogeneous effects of exposure to US technology on UK innovation across technology classes. In Panel Va, the unit of observation is a district-technology couple observed at decade frequency between 1870 and 1930; in Panel Vb, the same units are observed at yearly frequency over the same period. In Panel Va, each dot reports the coefficient of an interaction term between exposure to US technology and technology indicator variables; in Panel Vb, each dot reports the coefficient of an interaction term between technology dummies and an indicator variable that is equal to one for periods after the unit is exposed to a US innovation shock for the first time and zero otherwise. In both cases, the dependent variable is the log(1+) number of patents. In Panel Va, the underlying regression includes district-by-time and technology-fixed effects; in Panel Vb, the triple-differences model includes district-by-year, technology-by-year, and district-by-technology fixed effects. The estimated coefficients are plotted against the measure of revealed comparative advantage discussed in the main text. Loosely speaking, the UK is relatively more active than the US in technologies to the right of one, and it is less active than the US otherwise. Both plots superimpose a polynomial of degree two and report the estimated coefficients of the measure of revealed comparative advantage of orders one and two, along with their robust standard errors. The size of each dot reflects the number of patents issued in the UK over the sample period in each technology class. Referenced on page(s) 23.

FIGURE VI. Dynamic Effects of Family and Neighborhood Emigration



Notes. This Figure reports the impact of emigration to the United States on the innovation activity of their relatives in the United Kingdom (Panel VIa) and of their neighbors (Panel VIb). In Panel VIa, the unit of observation is an extended family defined as comprising all those who share the same surname in a given county. Families are observed at yearly frequency between 1870 and 1930. In Panel VIb, the unit of observation is an individual observed at yearly frequency between 1880 and 1900. The dots report the coefficients of an indicator variable that codes the period since the first emigrant in the family (Panel VIa) or in the neighborhood (Panel VIb). The black dashed line indicates the period when the treatment is first active; the last year before the treatment is active serves as the baseline category. The dependent variable is the log(1+) number of patents. All regression specifications control for unit (family or individual) and year fixed effects. Standard errors are clustered at the family (Panel VIa) and district (Panel VIb) level. The bands report 95% confidence intervals. Each Figure reports separate F-statistics for the joint significance of the pre- and post-treatment coefficients and associated p-values. Referenced on page(s) 28.

FIGURE VII. Dynamic Effect of the Transatlantic Telegraph Cable



Notes. This Figure reports the dynamic effects of the transatlantic telegraph cable(s) that connected the UK and the US in 1866 on innovation activity in the UK. The unit of observation is a district-technology class pair observed at a yearly frequency between 1853 and 1879. The analysis period is constrained by the patent data starting in 1853. The year 1879 is chosen to have a symmetric window around the first treatment period (1866). The dependent variable is the log(1+) number of patents. The dots report the coefficient of an interaction term between knowledge exposure in the 1870s and year dummies that code the period since the introduction of the first transatlantic telegraph cable in 1866. The dashed black lines mark the first cable and subsequent ones in 1873 and 1874. Years are grouped in two-year windows; the 1865- 1866 bin is the baseline category. The blue dots refer to the sub-sample of districts part of the British telegraph network. The red dots refer to the unconnected sub-sample. The regressions on both sub-samples include district-by-technology, technology-by-year, and district-by-year fixed effects; standard errors are clustered at the district level. Bands report 95% confidence intervals. Referenced on page(s) 32.