Organizational Practices and Technology Adoption:

Evidence from Jewish Immigration and the Tailoring Industry in England

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Abstract

This paper provides causal evidence on the role of organizational knowledge in driving technology adoption. Using newly constructed data on production tasks from six decades of English census records, we examine an exogenous shift in organizational practices in the English tailoring industry, prompted by the arrival of Jewish tailors fleeing pogroms in the Russian Empire (1881-1905). Specialized in ready-to-wear production before the sewing machine's arrival in the Russian Empire, Jewish tailors brought expertise in organizing production with a greater division of labor than the bespoke work dominant in England at the time. We study how this shift influenced the adoption of the sewing machine - introduced in England in the late 1860s - and the transition to ready-to-wear production. Augmenting our analysis with firm data, we show that Jewish tailors used the sewing machine to scale-up ready-to-wear production, establishing larger workshops with more machinists and specialized workers than native tailors. In response, native tailors adopted the machine more widely, along with the organizational practices of the immigrant workshops, accelerating the transition to ready-to-wear. Our findings imply that pre-existing organizational practices, like the division of labor, can foster the adoption of future technologies.

Keywords: organizational knowledge, technology adoption, immigration
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1 Introduction

The adoption of new technologies in production is at the core of economic development. Integrating new technologies often requires reorganizing production and introducing new organizational practices. Henry Ford's moving assembly line revolutionized car manufacturing by dividing labor into specialized tasks (Milgrom and Roberts, 1990). More recently, the arrival of the internet transformed office work by enhancing digital collaboration across teams. While complementary organizational practices are crucial for realizing the productivity potential of new technologies (Brynjolfsson et al., 2021), little is known about the role of organizational knowledge in technology adoption. Do firms with accumulated knowledge integrate new technologies faster? Understanding the role of organizational knowledge is key to identifying the factors that shape a firm's ability to incorporate new technology and modernize production.

The idea that there are gains from organizing production efficiently is a fundamental one in economics, dating back to Adam Smith's *division of labor* (Smith, 1776). Yet, evaluating the role of organizational knowledge in adopting new technology remains an empirical challenge. First, efficient organizational practices typically emerge through a process of trial and error after new technologies are introduced (Juhász et al., 2024), making it difficult to establish a causal link. An ideal experiment would require a shift in organizational practices independent of technology, allowing us to study how these practices influence adoption while holding technology constant. Such an experiment is hard to come by. Second, standard data sources rarely allow us to observe which specific technology is used in production, even more so to observe which workers operate the technology under the old and new organizational practices.

This paper overcomes these challenges by leveraging a newly constructed dataset with granular information on occupation that allows us to identify organizational practices in detail, and a unique historical episode that brings us as close as possible to the ideal experiment. We exploit the unexpected arrival of Jewish immigrant tailors in England between 1881 and 1905, who fled pogroms and discriminatory laws in the Russian Empire, as an exogenous shift in organizational practices in tailoring.

By the time Jewish tailors arrived in England, garment production was predominantly bespoke (Feldman, 1994). Native tailors were using the sewing machine - introduced in the late 1860's - to refine their craft and improve individual productivity. In contrast, Jewish tailors in the Russian Empire had long specialized in the standardized production of ready-to-wear (RTW) garments, even before the sewing machine became available (Wasserman, 2008).[1] This approach involved organizing production in larger workshops with a greater division of labor into specialized tasks, compared to bespoke work. Upon arriving in England, Jewish tailors used the readily available sewing machine to automate and scale-up the RTW production process (Figure A1).[2] We study how this shift in organizational practices influenced the adoption of the sewing machine and the transition to RTW production in the English tailoring industry.

For our empirical analysis, we construct a novel dataset using the universe of census records in England from 1851 to 1911, digitized by the I-CeM project (Higgs and Schurer, 2020). A key feature of these records is that respondents provided descriptions of their occupations, which were used by clerks to classify occupation at the industry level (e.g. "tailor"). Using textual analysis, we extract granular information on (micro-) occupations and reclassify tailors into three categories: sewing machinists, specialists performing tasks into which RTW production is divided, and generalists, whose descriptions only indicate the occupation of tailor. We assess the adoption of the sewing machine by measuring the proportion of machinists, and evaluate the shift to RTW production by comparing the share of specialists to generalists. Using information on country of birth, we compare adoption patterns between immigrant and native tailors.

We supplement our analysis with two further datasets. To examine the effect of adopting the RTW organization of production on firm size, we use data from the British Business Census of Entrepreneurs covering the period 1851 to 1911 (Bennett et al., 2017). Additionally, we recover the occupational profiles of the arriving immigrants back in the Russian Empire, utilizing arrival records from the Poor Jews' Temporary Shelter in London Database (Newman and Smith, 2008).

[1] Godley (2023) using Singer's sales data (90% market share in Russian Empire) shows that the machine was widely adopted in the Russian Empire only after 1903–1904, after our Jewish immigrants had left and settled in England.

[2] Due to discrimination, Jewish tailors were largely excluded from employment in workshops of native tailors. As a result, they established their own workshops, hiring fellow immigrants (Feldman, 1994).

We identify Jewish immigrants arriving in England as individuals born in the Russian Empire, and hereafter refer to them as Russian immigrants.[3] Due to low levels of capital and discriminatory laws, participation of Jewish people in capital-intensive industries and services in the Russian Empire was restricted. Consequently, small-scale manufacturing, particularly of cheap ready-to-wear garments, became their most common sector of employment (Kahan, 1986). Throughout our period of study, approximately 140,000 immigrants fled the Russian Empire and settled in England (Godley, 2001), with records from the Temporary Shelter confirming that 26% of them had worked as tailors in the Russian Empire. The tailoring industry thus reasonably emerged as the primary source of employment for the Russian immigrants in England, absorbing 27% of the influx, while employing only 3% of the native labor force - a labor supply shock equivalent to 5% of the industry's native workforce in 1881.

First, we establish empirically that the arrival of Russian tailors constituted a shift in organizational practices in tailoring, with them specializing in RTW more than natives at the time. We show that upon arrival in 1881, a larger proportion of Russian tailors worked as sewing machinists and specialists, while native tailors primarily worked as generalists. Using our firm data, we find that in 1881 Russian tailors owned larger workshops with more employees, whereas native tailors typically ran small workshops with 1 to 3 employees or were self-employed. Our findings reveal the distinct organization of production in Russian immigrant workshops, characterized by a greater division of labor and a focus on RTW production.

With respect to native tailors, they experienced a stark rise in the share of machinists during the years of Russian immigrant arrivals, from just under 2% in 1881 to over 10% in 1911. This was accompanied by a similar rise in specialists and a decline in generalists, indicating that native tailors increasingly adopted both the sewing machine and the organizational practices of Russian immigrant workshops.

To identify the causal effect of the arrival of Russian tailors on the adoption of the sewing ma-

[3]Given that Jewish immigration was the only significant migration episode between the two countries during that period, our strategy credibly identifies the inflow of Jewish immigrants.

chine and the RTW organization of production, we compare decennial changes in the shares of machinists, specialists and generalists in tailoring across districts in England, relative to the district's inflow of Russian tailors. While the reasons Russian tailors fled the Russian Empire were exogenous to technological progress in England, an endogeneity problem arises if they disproportionately settled in districts where the machine had already been adopted more widely, especially given its importance for scaling up RTW production.

We address this concern by employing a standard approach in the immigration literature (Card, 2001). We predict district inflows of Russian tailors in 1881 using settlement patterns of Russian tailors in 1851, a time when the sewing machine was not yet in use, and garment production was largely homogeneous, with over 99% of tailors working as generalists.[4] A potential threat to this identification strategy arises if the geographical distribution of Russian tailors in 1851 closely resembled that of native tailors, as districts with a longer-established English tailoring industry may have been more likely to adopt the sewing machine by 1881. We explicitly show that this was not the case, as the location of native tailors in 1851 fails to predict district inflows of Russian tailors in 1881. Native tailors in 1851 were concentrated in Manchester and central London, while Russian tailors settled in the East End of London and Leeds, where future arrivals also concentrated. Additionally, we test for the correlation between our instrument and local wealth levels, as wealth could be predictive of technological progress or demand for garments. We find no significant correlation, reinforcing the validity of our instrument.

First, regarding the sewing machine, our findings demonstrate that the arrival of Russian tailors significantly expedited its adoption within the English tailoring industry. This outcome is attributed to both substantial inflows of Russian sewing machinists and to an increase in the proportion of machinists among native tailors. For every Russian tailor who arrived in England, an additional 0.05 native tailors began working as sewing machinists. While immigrants adopted the machine more widely upon arrival, native tailors also increased their adoption in

[4] While we demonstrate the relevance of our instrument in Section 4, it is worth noting that most Russian tailors in 1851 were likely Jewish. Gartner (1960) shows that over 85% of Russians in England in 1871 were Jewish, and he notes that this was the case for most Russians in England in the mid-19th century.

response to the immigration shock.

Second, the wider adoption of the sewing machine by native tailors came together with a shift in their production organization, influenced by the practices of Russian workshops. We find a significant increase in the share of specialists among native tailors in districts where Russian tailors settled, alongside a decrease in the proportion of generalists. Specifically, for every two generalist native tailors displaced by the arrival of Russian tailors, one additional native tailor began working as a specialist and another as a sewing machinist. The rise in the share of native tailors performing specialized tasks indicates that the arrival of Russian tailors compelled natives to adopt the RTW organization of production characterized by a greater division of labor.

Third, using our firm data, we show that this result was also reflected on the size of the native tailoring firm. We first find a significant displacement effect on self-employed native tailors, who likely specialized in bespoke production. Second, in districts where the Russian tailors settled, the number of native tailors working as employees increased substantially. With the total number of native employers remaining unchanged, we find that the arrival of Russian tailors led to a 16% increase in the average size of the native tailoring firm. As Russian immigrants were not hired by native tailors, due to issues of discrimination, this result is driven by native tailors re-organizing production within their firm.

These results suggest that the shift in organizational practices caused by the arrival of Russian tailors accelerated the adoption of the sewing machine and catalyzed the expansion of the ready-to-wear production process in England. The optimization of production in Russian immigrant workshops led to lower prices and improved product quality of ready-to-wear garments (Feldman, 1994). Even though bespoke and ready-to-wear garments cannot be considered as perfect substitutes, this shift lowered the cost and increased the availability of affordable good-quality clothing. This compelled native tailors to adopt the same production process, and to eventually enter the ready-to-wear market as well. The immigrant workshops were not examples of modern industrial facilities. They were characterized by extensive sub-contracting, long working hours and unhygienic environments within the confined living spaces belonging to immigrant households (Feldman, 1994). However, our results demonstrate that they contributed to the establishment of a more modern production process in the tailoring industry at the time.

Our findings underscore the role of organizational knowledge as an important initial condition for adopting new technologies in production. Jewish tailors, having developed a system of garment production with a greater division of labor in the Russian Empire — before the sewing machine was invented — were able to integrate the machine more swiftly than natives when they arrived in England. This accelerated the industry's transformation toward ready-to-wear. Reorganizing production is typically seen by firms and policymakers as a necessary complementary investment to fully integrate new technologies. However, our results suggest that pre-existing organizational practices, being not inherently technology-specific, can enhance a firm's capacity to adopt future technologies. For example, large-scale manufacturers that have implemented just-in-time manufacturing are better positioned to integrate robotics, as both systems require a more specialized division of labor. Similarly, businesses with established cross-functional teamwork can more easily adopt collaborative tools like Slack or Microsoft Teams, which enhance coordination among team members. Our findings emphasize the value of investing in organizational practices to boost firm's adaptability to upcoming technological advancements.

Related literature and contributions. Our work contributes to several strands of the literature. First, it is related to an extensive literature that emphasizes the need to reorganize production to maximize the productivity potential of new technologies (David (1990), Bresnahan and Trajtenberg (1995), Brynjolfsson and Hitt (2000), Bresnahan et al. (2002), Hall and Khan (2003), Bloom et al. (2019), Giorcelli (2019), Juhász et al. (2024)). Recent work has also shown how a variety of organizational barriers can impede technology adoption (Atkin et al. (2017), Feigenbaum and Gross (2024)). To our knowledge, this is the first paper to empirically isolate the role of organizational knowledge in driving technology adoption. Taking advantage of the sudden arrival of Russian tailors who specialized in a different organization of production than natives, we break the reverse causality link between the arrival of new technologies and establishment of new organizational practices. Additionally, relative to the rest of this literature, our work draws on a new dataset that opens the "black-box" of production for the first time, allowing us to observe the specific task each worker performs and to analyze how the sewing machine - a new technology at the time - was operated under distinct organizational practices.

Second, we contribute to a growing literature examining the impact of immigration on technology adoption. Recent studies in this field have used patent data (Andersson et al., 2022; San, 2023; Doran et al., 2024) or data on capital equipment (Lewis, 2011; Hornbeck and Naidu, 2014; Coluccia and Spadavecchia, 2024), to analyze how different immigration shocks influence technical change. The underlying assumption in this body of work is that immigration affects adoption through a static production framework, with adoption increasing if the incoming labor is complementary to technology. However, recent theoretical (Acemoglu and Restrepo, 2018, 2019) and empirical work (Lin, 2011; Autor et al., 2024) has shown that technology adoption often generates dynamic shifts in the content of work, with old tasks eroding and new tasks emerging in the production process. Building on this, our findings show that immigration, through its influence on technology adoption, can affect the content of work itself, with important implications for native employment. Specifically, although the arrival of Russian tailors displaced native generalist tailors, it simultaneously created job opportunities for natives in the new specialized tasks required in RTW production. While further research is required to fully explore how immigration affects native employment through its impact on technology adoption, this paper highlights this channel and makes an important first step in this direction.

Third, our research relates to a burgeoning literature exploring how human mobility fosters the diffusion of novel knowledge across countries (Kerr, 2008; Hornung, 2014; Moser et al., 2014; Bahar et al., 2022, 2024; Prato, 2022; Moser and San, 2023; Coluccia and Dossi, 2024). While much of the existing work has focused on the transfer of scientific knowledge or patent-related innovations, we introduce organizational knowledge as a key form of expertise that can also be transmitted and shape outcomes in the receiving country. Moreover, Russian tailors were only able to apply their expertise and scale up RTW production in England, where the sewing machine was readily available, but could not do so back in the Russian Empire, where such technology was lacking. This demonstrates that local economic conditions play a decisive role in determining how effectively transmitted knowledge can be applied in the receiving country.

Fourth, this paper is related to a literature that studies the role of competition as a driver of technology diffusion (Schmitz (2005), Aghion et al. (2005), Bloom et al. (2016)). Much of the existing research in this area tends to focus on aggregate total factor productivity (TFP) or labor productivity as outcomes, while direct studies on the diffusion of specific technologies or organizational practices remain limited (Bryan and Williams, 2021). Our paper addresses this gap by using a novel dataset to provide a direct empirical study on the diffusion of organizational practices, considering the establishment of Russian tailoring workshops as a competitive force that influenced native tailors to adopt new practices.

Lastly, our findings contribute to a literature in economic history that has examined the relationship between technological advancements and skill in the 19th century (Hounshell, 1984; Sokoloff, 1984; James and Skinner, 1985; Cain and Paterson, 1986; Atack, 1987). These studies argue that, during that period, as manufacturing shifted away from highly-skilled artisans to larger workshops and factories, technological advances and physical capital functioned as substitutes for skilled labor while complementing unskilled manual labor.[5] Although data limitations prevent us from directly measuring the skill level of either native bespoke tailors or incoming Russian tailors, our results based on highly granular data on production tasks and on firm size, provide direct empirical evidence supporting this argument. Specifically, we find that the arrival of Russian tailors which accelerated the adoption of the sewing machine in the tailoring industry, also displaced self-employed native tailors - likely specialized in bespoke work - and drove the transition of garment production to larger workshops.

The remainder of the paper is organized as follows. Section 2 describes the historical context. Section 3 delves into the data, while Section 4 outlines our empirical strategy and discusses its

[5]For a comprehensive discussion on the evolution of technology-skill complementarity from the 19th to the 20th century, please refer to Goldin and Katz (1998). Following the terminology in their paper, we refer to the term 'artisan' as a worker who produces nearly the entire product within a production process characterized by minimal division of labor, similar to the bespoke tailors of 19th-century England.

validity. Section 5 presents the results. Section 6 discusses our findings. Section 7 concludes.

2 Historical Background

2.1 Jewish people in the Russian Empire and migration to England

Following the partitions of Poland (1772, 1793, and 1795) and the Congress of Vienna (1815), the Russian Empire acquired territories that had been home to the world's largest Jewish community since the 14th century. According to estimates presented in (Grosfeld et al., 2020) based on the 1897 Russian Census, 5.2 million Jewish people lived in the Russian Empire, with 4.8 million concentrated in the Pale of Jewish Settlement - the region where Jewish people were legally restricted to reside.[6] Within the Pale, crafts dominated Jewish employment, accounting for 25% of the labor force, with tailors and cobblers being the two most common occupations. Jewish tailors had long been involved in the production of RTW garments. In fact, Wasserman (2008) notes that Jewish tailors in Warsaw, then part of the Pale, were already specializing in RTW as early as 1795, long before the invention of the sewing machine.

Between 1881 and 1882, the first wave of anti-Jewish mob violence (pogroms) broke out. Incidents ranged from disturbances, such as the smashing of windows in Jewish homes, to violent outbursts that included assaults and pillaging of Jewish property (Aronson, 1980). The majority of pogroms took place within the Pale, but there were riots in other parts of the Russian Empire too. There were three waves of pogroms. The first one occurred between 1881 and 1882, the second between 1903 and 1906, and the third in 1917. A consequence of the pogroms was the introduction of the May Laws in 1882. The laws primarily prohibited Jews from migrating from urban centres to rural areas within the Pale and restricted their involvement in the real estate and the mortgage market.[7] Pogroms and the May Laws triggered a large wave of Jewish emigration from the Russian Empire with more than 2 million Jewish people fleeing the Russian

[6] The Pale was a western region in the Russian Empire with varying borders that existed from 1791 until 1917. It eventually consisted of parts of contemporary Russia, Poland, Ukraine, Latvia and Lithuania and the whole of Belarus and Moldova. For a map of the Pale please see Grosfeld et al. (2013).

[7] Although initially intended as temporary measures, they were followed by additional discriminatory legislation in subsequent years and they remained in force until 1917.

Empire between 1881 and 1920.

While the majority of these immigrants moved to the United States, approximately 7% settled in the United Kingdom (Godley, 2001). Most of them established themselves in England, with an estimated 70% concentrated in London's East End, in the districts of Whitechapel, Spitalfields, Saint George in the East (now part of the London Borough of Tower Hamlets), and Stepney. Our estimates suggest that the number of working-age (15-65) Russian immigrants in England increased five-fold between 1881 and 1901, by roughly 61,000. This figure represented 0.4% of the working-age population in England in 1881. Although pogroms continued after 1901, the passage of the Aliens Act in 1905 significantly restricted inflows of immigrants from the Russian Empire.

2.2 The tailoring industry in England

In 1881, clothing was the fourth largest sector of employment in England (Figure A2), consisting of three main industries: tailoring, shoe-making, and hat-making. The majority of workers in this sector were employed in tailoring, with Russian immigrants particularly over-represented in this industry (Figure A3). While tailoring accounted for approximately 4.8% of the native labor force in England, it absorbed around 30% of the Russian immigrants arriving during our period of study. For this reason, tailoring is the focal point of analysis in this paper.

Before the invention of the sewing machine, most garment production in England's tailoring industry was bespoke. RTW production was fairly limited and largely restricted to the production of military uniforms (Godley, 1997). For those unable to afford bespoke clothing, the primary alternative was the second-hand clothing market, which provided cheaper garments to a broader segment of the population. When the sewing machine became available, native tailors specializing in bespoke production adopted it to enhance individual work. In contrast, Russian tailors who arrived in England made the sewing machine a central component of the organization of production in the workshops they established, using it to scale up manufacturing of RTW garments.

The sewing machine was first patented in England by William Thomas in 1841. However, it was not until the late 1860s that sales began to rise, after the Singer Company opened its first factories in Glasgow to mass-produce sewing machines. By the early 1880s, when Russian immigrants arrived, the cost of renting a sewing machine was 2 shillings and 6 pence per week - a price easily affordable for Russian tailoring workers in the East End of London, who earned wages at least 9 times that amount (Pilzer, 1979; Feldman, 1994). As a result, working for a few weeks in the tailoring workshops of fellow immigrants, allowed newly arrived Russian tailors to acquire enough capital to start renting sewing machines and establish their own tailoring workshops, usually in their flats.

The RTW production process in which these workshops specialized featured a significantly finer division of labor, with workers assigned to specialized tasks, and higher levels of automation compared to bespoke production. Using information from Dictionary of Occupational Terms in Great Britain Ministry of Labour (1927), we compare the two processes in Figure 1. In both cases, production began with the cutter, responsible for precisely cutting garment pieces to match the required sizes of the final product. In bespoke production, this role was particularly crucial, as each cut had to correspond exactly to the unique measurements of the customer, unlike in RTW, where cuts followed standardized dimensions. In bespoke tailoring, the cutter would pass the garment to the tailor, who would complete all the remaining tasks, including basting, sewing, pressing, and finishing (e.g., felling, buttonhole making, zipper installing).[8] In contrast, in the RTW production process in which Russian workshops specialized, all the tasks performed individually by the bespoke tailor, were instead divided across specialized workers. Consequently, while workshops owned by native tailors were primarily staffed by the main tailor and one or two assistants, Russian workshops employed more workers (machinists, pressers, basters etc.) and featured a more structured organization of production, typically overseen by a master tailor or supervisor.

[8]Basting: stitching pieces of the garment together in preparation for sewing. Pressing: ironing of completed garments to give finished appearance.

3 Data and descriptive statistics

3.1 Data

Our main analysis relies on the new variable of micro-occupations, which we construct from the census records. Data on firm identifiers and size is sourced from the British Business Census of Entrepreneurs, while records from the Poor Jews' Temporary Shelter in London provide information on the occupations immigrants held in the Russian Empire before arriving in England.

Micro-occupations. The census data from 1851 to 1911, excluding 1871, include 160 million individual records.[9] A notable feature of these censuses is that respondents were asked to provide descriptions of their occupations, which clerks later used to track occupation at the industry level (e.g. tailor). When census records were digitized by the I-CeM project Higgs and Schurer (2020), both the industry classification and the occupational description for every individual were retained.

Table 2 presents an example of the dataset. All workers in this example are classified as tailors in the first column. However, in their original census responses, illustrated in the second column, a new level of granularity is revealed: the first individual worked as a presser, the second as a sewing machinist and the third as a button-hole maker. Using a text-search algorithm, we process these census responses and construct a new variable of micro-occupations, in which we reclassify tailors accordingly.[10] The new variable allows us to identify tailors working as sewing machinists, those performing specialized tasks within the RTW production process, and those whose responses provided no further detail, categorized as generalists. As our novel variable is derived from census records, we are able to discern the country of birth of each worker and compare how Russian and native tailors integrated the sewing machine and the RTW organizational practice into production.

[9] Unfortunately, the 1871 census for England and Wales is not included in the I-CeM project.
[10] For details about the data construction process please see Appendix X1.

Firm data. The British Business Census of Entrepreneurs 1851-1911 is a dataset linked to the census records digitized by I-CeM (Bennett et al., 2017). It indicates whether an individual is self-employed, an employer (a firm owner with employees), or an employee. For the period 1851-1881, the data also provide direct information on the workforce size of businesses owned by employers. To assess how the adoption of the RTW process influenced firm size after 1881, we compare the evolution in the number of employees relative to the number of employers and self-employed individuals in the tailoring industry.

Immigrant occupations in the Russian Empire. The Poor Jews' Temporary Shelter in London served as a point of first contact and a temporary refuge for Jewish immigrants arriving from the Russian Empire between 1896 and 1914. The database contains 60,000 arrival records digitized by Newman and Smith (2008), with 30,000 of these records concentrated in the first five years of the shelter's operation, from 1896 to 1901. More than 23,000 of the records from that period include information about the immigrants' occupations in the Russian Empire, likely recorded by clerks to assist with the job placement of newly arrived immigrants. Compared to census estimates, these records represent approximately 55% of the working-age immigrant inflow from the Russian Empire to England between 1891 and 1901, providing a representative sample of the arriving immigrant population.

3.2 Russian immigrants in England

Table 2 presents the occupational composition of Russian immigrants in their country of origin, as reflected on the Shelter's records. Consistent with the occupational distribution of Jewish people in the Pale of Settlement, as detailed in Grosfeld et al. (2020), 23% of the immigrants had experience in commercial occupations, while 26% were employed as tailors in the Russian Empire. This makes tailoring the most common occupation among the immigrant inflow, indicating that the immigrants brought considerable expertise in the tailoring industry. Additionally, as the occupational distribution of arriving immigrants closely mirrors that of Jewish workers in the Russian Empire, our findings suggest there was no occupational selection bias among those who migrated to England.

Figure 2 utilizes the census data to plot the shares and net inflows of Russian immigrants in the working age population (top) and the tailoring workforce (bottom). The similarity between the bottom and top figures highlights that tailoring became the primary source of employment for Russian immigrants in England, consistent with tailoring being their most common occupation in the Russian Empire. While the majority of immigrant inflows into tailoring occurred between 1881 and 1901, some Russian tailors had already arrived by 1881, representing 1% of the tailoring workforce. As the number of Russian immigrants working in tailoring grew by approximately 16,000, this share increased to 4% by 1901. The figures on the right reflect the restriction of immigrant inflows from the Russian Empire due to the Aliens Act of 1905, with the number of Russian tailors in England increasing by only 1,000 between 1901 and 1911.

3.3 A shift in organizational practices in tailoring

In this sub-section, we present summary statistics documenting the shift in organizational practices within the tailoring industry. First, we demonstrate that upon their arrival in 1881, Russian tailors in England disproportionately specialized in RTW compared to native tailors. Second, we track the adoption of the sewing machine and the RTW production process during the years of these immigrant arrivals.

Figure 3 utilizes our new variable to compare the shares of machinists and specialists among Russian immigrant tailors with those of native and other immigrant tailors in 1881. Approximately 3% of Russian tailors worked as sewing machinists and another 3% as specialists, while these shares among native tailors were below 1% for both categories. As a direct result, the proportion of generalists was higher among native tailors than among Russian tailors.

Figure 4 leverages the last year in which firm size is directly observable in our data, and compares the size of workshops owned by Russian tailors to those owned by native tailors in 1881. Following the descriptions provided in Feldman (1994), we define workshops as firms with

40 or fewer employees.[11] Russian tailors were more likely to own larger workshops, with over 60% employing more than 4 workers, whereas the same share among natives was below 40%, with the majority employing between 1 and 3 workers. Figure A4 in Appendix further shows that more than 80% of native tailoring entrepreneurs were self-employed, compared to 50% of Russian tailors.

Figure 5 plots the evolution of the share of machinists among Russian immigrants in tailoring, alongside that of natives and other immigrants from 1851 to 1911. Initially, the use of the sewing machine was minimal, with all three groups showing shares close to zero until 1861. In line with figures presented in Godley (2023) on sales of the sewing machine, there was a surge in the shares of sewing machinists between 1861 and 1881. Even in these early stages of adoption, and throughout the period covered by our study, the proportion of machinists was consistently higher among Russian tailors than among their native counterparts. However, in the three decades following 1881, we observe a significant rise in the proportion of machinists among both Russian and native tailors, with their shares reaching 24% and 10% by 1911 respectively.

The increase in the adoption of the sewing machine went hand in hand with the expansion of the RTW production process, as this is reflected on the tasks tailoring workers performed in production. Figure 6 illustrates the evolution of the share of specialists, while Figure 7 shows that of the share of generalists. The patterns in these figures closely mirror the trends in the share of machinists. Until 1861, when the sewing machine was not in use, the share of specialists was near zero, with over 99% of tailors working as generalists. In the years of the widespread adoption of the machine from 1881 onwards, the share of specialists grew and the share of generalists sharply decreased. Reflecting their broader adoption of the machine and the RTW process, Russian tailors consistently showed a higher share of specialists and a lower share of generalists compared to native tailors.

[11] Feldman (1994) notes that Mark Moses, who ran one of the largest RTW workshops in 1888, employed 40 workers. By 1898, during the expansion of RTW, the average tailoring workshop in England employed around 30 workers.

4 Empirical strategy

To estimate the causal effect on the adoption of the sewing machine and the RTW process, we compare adoption rates across 554 districts in England, relative to each district's inflow of Russian tailors. More specifically, we first regress the decennial changes in the ratios of machinists, specialists and generalists over native workers in the tailoring industry on the decennial change in Russian-to-native ratio in tailoring. Then, to examine the impact on the size of native tailoring firms, we estimate the same regression using the decennial changes in the shares of employees, employers, and self-employed among native tailors as the outcome variables. Figure 8 presents the distribution of the inflow of Russian tailoring workers across districts in England, illustrating the variation we leverage for identification. For robustness, we estimate the specification below separately for the two decades of Russian immigration, 1881-1891 and 1891-1901.

$$\Delta\left(\frac{Y_{st}}{N_{st}}\right) = \alpha + \beta * \Delta\left(\frac{R_{st}}{N_{st}}\right) + \gamma * \Delta X_{st} + \Delta\varepsilon_{st} \tag{1}$$

Δ denotes decennial change, s denotes district and t the census year. Y_{st} is the outcome variable of interest, denoting the number of machinists, specialists and other tailoring roles, N_{st} and R_{st} are the numbers of native and Russian workers in the tailoring industry respectively. ΔX_{st} controls for the change in the average age of workers in the district, α controls for time-trends, and $\Delta\varepsilon_s$ is an error term.

Although the reasons for emigration from the Russian Empire were exogenous to technological progress in England, an endogeneity problem would still arise if Russian tailors, recognizing the sewing machine's importance for scaling up RTW production, sorted into districts where the machine had already been adopted more widely. In this case, our OLS estimate of β would be upward-biased for the regressions estimating the impact on the shares of sewing machinists and specialists, and downward-biased for the regression estimating the effect on the share of generalists.

To address this issue, we apply a standard approach from the immigration literature (Card, 2001, 2009): we instrument district inflows of Russian tailors - separately for each decade - with the settlement patterns of Russian tailors in 1851. The underlying idea is that Russian tailors tended to settle in districts where other Russian tailors had already established themselves, and that these historical settlement patterns were independent of sewing machine adoption thirty years later (Bartel, 1989; Jaeger, 2007). The validity of our shift-share instrument relies on the exogeneity of the shares of Russian tailors across districts in 1851 (Goldsmith-Pinkham et al., 2020), since these are drawn from a period when the sewing machine was not yet in use (Figure 5), and tailoring production was largely homogeneous, with most tailors classified as generalists (Figure 7). We define ΔR_t as the nationwide decennial inflow of Russian immigrant tailors, and $\lambda_{s,1851}$ as the share of Russian tailors concentrated in district s in 1851. By multiplying the district share by the immigrant inflow, and scaling it by the number of native tailors in the district in 1851, we construct our instrument as the predicted inflow of Russian immigrant tailors in district s in census year t denoted as follows:[12]

$$\frac{\lambda_{s,1851} * (\Delta R_t)}{N_{s,1851}} \tag{2}$$

Table 3 presents results from the first stage regressions for each decade. The F-statistics—379.28 for the first decade and 435.95 for the second—indicate that the instrument is strong in both cases. Another potential threat to identification with this instrumental variable strategy arises if the settlement patterns of Russian tailors in 1851 matched the geographical distribution of native tailors in the same year. In such a scenario, our estimate of β would likely be biased, as districts with a higher concentration of English tailors in 1851 were more likely to have adopted the sewing machine by 1881. Table B1 in Appendix presents the results from a first stage regression, where we predict the district-level inflows of Russian tailors using the shares of native tailoring

[12] Card (2009) scales the shift-share instrument by regional employment in year $t-1$ ($N_{s,t-1}$). This ensures a first-stage coefficient of 1 if the Russian immigrants who entered tailoring between year t and $t-1$ made the same location choices as the incumbent Russian tailors in 1851. Our modified version allows for expressing the instrument as $\frac{R_{s,1851}}{N_{s,1851}} \times \frac{\Delta R_t}{R_{1851}}$, an interaction between a "share" and a "shift" component, in line with recent insights from the shift-share design literature (Goldsmith-Pinkham et al., 2020; Borusyak et al., 2022).

workers across districts in 1851. The low F-statistics for both decades demonstrate that the location of native tailors in 1851 does not predict the inflows of Russian tailors 30 years later. This can be explained by the fact that, in 1851, native tailors were concentrated in Manchester and central London, while Russian tailors were largely based in districts in London's East End and Leeds, where most immigrant tailors settled between 1881 and 1901, as shown in Figure 8.

Lastly, we test for any correlation between our instrument and district wealth levels in 1851. Wealth could be a confounding factor in our estimation through two channels. First, wealthier districts may have provided more favorable economic conditions for immigrants, including greater access to capital for renting sewing machines. Second, districts with lower levels of wealth may have experienced higher demand for the affordable RTW garments in which Russian tailoring workshops specialized. To proxy district wealth levels, we use the Historical International Standard Classification of Occupation (HISCO) system, assigning social status at the individual level based on occupation. We identify the top and bottom 10% of occupations in the social status distribution and calculate the share of individuals in each district holding occupations in these deciles. The results, presented in Table B2 in the Appendix, show no correlation between the settlement patterns of Russian tailors in 1851 and district wealth levels, further supporting the validity of our instrument.

5 Results

Our findings are presented in the following order. First, we report the estimated impact on the adoption of the sewing machine. Next, we present results on the adoption of the RTW production process, focusing on the effects on the shares of specialists and generalists. Finally, we show results on the effect of Russian tailors' arrival on the size of the native tailoring firm.

Adoption of the sewing machine. Table 4 presents the results from estimating specification (1), with the ratio of machinists to native tailoring workers as the outcome variable. Panel A reports the overall effect on the tailoring industry, combining both the inflows of Russian machinists and changes in the share of machinists among native tailors. In this case, the numerator of the outcome variable includes both Russian and native machinists. Panels B and C break down these forces, estimating the impact separately for Russian and native machinists.

The results demonstrate that the arrival of Russian tailors significantly accelerated the adoption of the sewing machine in the tailoring industry. In Panel A, the estimates suggest that for every Russian tailor arriving in England during each decade, more than 0.2 tailors began working as machinists. With the total inflow of Russian tailors representing 5% of the native tailoring labor force in 1881, this influx led to a 1 percentage point increase in the overall share of machinists.

Panel B reveals that a significant portion of the effect comes from the inflow of Russian machinists themselves, with over 16% of the arriving Russian tailors working as machinists. However, comparing these results to Panel A indicates that the overall effect cannot be fully explained by the inflows of Russian machinists alone. In Panel C, we find that for every Russian tailor arriving in England, an additional 0.05 native tailors started working as machinists. This corresponds to an increase of 0.25 percentage points in the share of native machinists — equivalent to 1/4 of the standard deviation. Although immigrants adopted the sewing machine more extensively upon their arrival, native tailors further incorporated the technology into their production in response to the immigration shock as well.

Adoption of RTW organization of production. Table 5 presents estimates of inflows of Russian specialists and generalists in Panels A and B, respectively. These estimates are obtained by estimating equation (1), with the ratios of Russian specialists and generalists over native tailors as outcome variables. The results are then compared to the corresponding average shares of native tailors across districts, reported in the bottom row of each panel. The comparison reveals the stark contrast in specialization in RTW between the incoming Russian tailors and the incumbent native tailors. While, on average, only 1% of native tailors were employed as specialists at the base year, approximately 20% of the Russian inflow over the two decades found employment in specialist roles. Conversely, only 60% of the Russian inflow worked as generalists, compared to 98% of native tailors who were generalists at baseline.

Turning to the impact of these inflows on the organization of production among native tailors, Table 6 reports the estimated effects on the shares of native specialists (Panel A) and native generalists (Panel B). The results clearly indicate that the arrival of Russian tailors spurred the adoption of the RTW organization of production by native tailors. First, we find that, consistently across both decades, each Russian tailor's arrival led to 0.05 more native tailors performing specialized tasks characteristic of the RTW process, reflecting an increase of 0.25 percentage points in the share of native specialists (1/3 of the standard deviation at the base year). Second, the estimates in Panel B show a significant displacement effect on native generalists. For every Russian tailor that arrived, 0.1 native generalists were displaced, leading to a cumulative 0.5 percentage point reduction in the share of native generalists (1/4 of standard deviation) throughout our period of study. When examining the overall impact on the organization of production among native tailors, by taking into account both these findings and our earlier estimates on sewing machinists, our results show that for every two native generalists displaced by the arrival of Russian tailors, one started working as a sewing machinist and one as a specialist.

The size of the native tailoring firm. In addition to a greater division of labor into specialized tasks, the RTW process required organizing production in larger workshops, with a greater number of employees. Our findings, based on the micro-occupation variable, demonstrate that native tailors responded to the immigration shock by adopting the more specialized division of labor characterizing the production of RTW garments. Was this shift also reflected in the size of the workshops they owned? Unfortunately, as mentioned earlier, our firm data provide direct information on the number of employees working for each employer (firm owner) only up until 1881. However, since native tailors typically did not hire Russian immigrant workers due to issues of discrimination (Feldman, 1994), we can infer the impact on the size of native workshops by comparing the effect on the number of native employees to the effects on the numbers of native employers and self-employed tailors, for which we have data beyond 1881.

Using our main specification, we regress the shares of employees, employers and self-employed among native tailoring workers on the district inflow of Russian tailors. Table 7 presents the results from these regressions. Panel A reports the effects on the share of employees, Panel B on the share of employers, and Panel C on the self-employed. The results show that the arrival of Russian tailors had a significant positive effect on the size of the native tailoring firm. We find that an influx of Russian tailors equivalent to 1% of the native tailoring workforce increased the share of native tailoring employees by 0.15%. Since the estimates in Panel B show no change in the share of employers in response to the immigration shock, we infer that the size of native firms grew. Specifically, we estimate that the arrival of Russian tailors between 1881 and 1901 increased the average size of native tailoring firms by 16%.

Finally, the estimates reported in Panel C, indicate a significant displacement effect on native tailors who were self-employed, with the magnitude of the effect matching the increase in the share of employees. The effect corresponds to an approximate 0.75 percentage point decrease in the share of self-employed native tailors from 1881 to 1901. Given that self-employment in tailoring was largely associated with bespoke production, this finding further underscores how the arrival of Russian tailors accelerated the industry's transition to RTW production.

6 Discussion

The results clearly demonstrate that the organization of production established in the workshops of Russian tailors was eventually adopted by native tailors. Having specialized in the standardized production of garments back in the Russian Empire, Russian tailors brought with them valuable organizational knowledge (*know-how*) of dividing garment production into specialized tasks. By implementing this organization of production in England, where the sewing machine was available, they were able to scale up RTW production and drive a shift in organizational practices across the tailoring industry.

Economists and policymakers have long argued that the absence of complementary organizational practices and knowledge poses a critical barrier to technology adoption (OECD, 2016; Cirera and Maloney, 2017). Our paper provides direct empirical evidence on this mechanism. Russian tailors, with their expertise in organizing production into specialized tasks, integrated the sewing machine into their workflows more rapidly than native tailors. Combining the arrival of new technologies, such as the sewing machine at the time, with the establishment of complementary organizational practices is crucial for maximizing the productivity impact of these technologies.

However, our findings shed light to a further key insight: organizational knowledge can serve as a precursor to technology adoption. Practices like the division of labor, cross-functional teamwork, improved data management systems, and factory-based workflows, are not tied to specific technologies but are vital for implementing a wide range of innovations. The Russian tailors back in the Russian Empire organized production with a greater division of labor at a time when the sewing machine had not yet been invented. Their organizational knowledge gave them an advantage when it came to successfully integrating the sewing machine later on. In the same spirit, businesses that have adopted lean production processes are better equipped to integrate robotics, as both systems benefit from precise workflows and automation. Businesses with established cross-functional teamwork can more easily adopt digital collaborative tools, which enhance coordination among team members. Establishing modern organizational practices not only allows firms to use new technologies more efficiently but also strengthens their ability to adopt future innovations.

7 Conclusion

The adoption of new technologies often necessitates adjustments in the organization of production. While it is well recognized that complementary organizational practices are essential for maximizing the productivity impact of new technologies, empirical evidence on the role of organizational knowledge in driving technology adoption remains sparse. First, because production organization typically adjusts after new technologies are introduced, making it difficult to establish a causal link. Second, standard data sources rarely allow the identification of specific technologies and organizational practices used in production.

This paper addresses these challenges using newly constructed data on production tasks from the English census records between 1851 and 1911, and examining an exogenous shift in organizational practices in the English tailoring industry, prompted by the arrival of Jewish tailors fleeing pogroms in the Russian Empire between 1881 and 1905. There are three takeaways from this study. First, organizational knowledge is a key driver of technology adoption, and established organizational practices enhance adaptability to future innovations. Second, immigration can affect native employment in the long-run through its influence on technical change. The arrival of Russian tailors displaced native bespoke tailors but also created new job opportunities in the tasks emerged from the shift to RTW production. Third, local economic conditions play a key role in determining how effectively transmitted knowledge impacts economic outcomes in the receiving country. Russian tailors were only able to apply their organizational expertise to scale up RTW production in England, where the sewing machine was readily available, but not in the Russian Empire, where this technology had yet to be introduced.

The paper identifies two potential areas for future research. First, our work shows that organizational knowledge is critical for the diffusion of new technologies. While the literature on the economics of innovation has studied the diffusion of new inventions and technologies across firms and space, the diffusion of modern organizational practices and the barriers to their adoption remain largely unexplored and merit further investigation. Second, this paper shows that immigration, by influencing the direction of technical change, can have a direct impact on the content of work, with important implications for native employment in the long term. The economics of migration literature has widely studied the impact of immigration on native employment and technical change separately. Further studies using detailed data on occupations and technology adoption within firms and industries should jointly examine these effects to advance our understanding of immigration's long-run impact on native employment.

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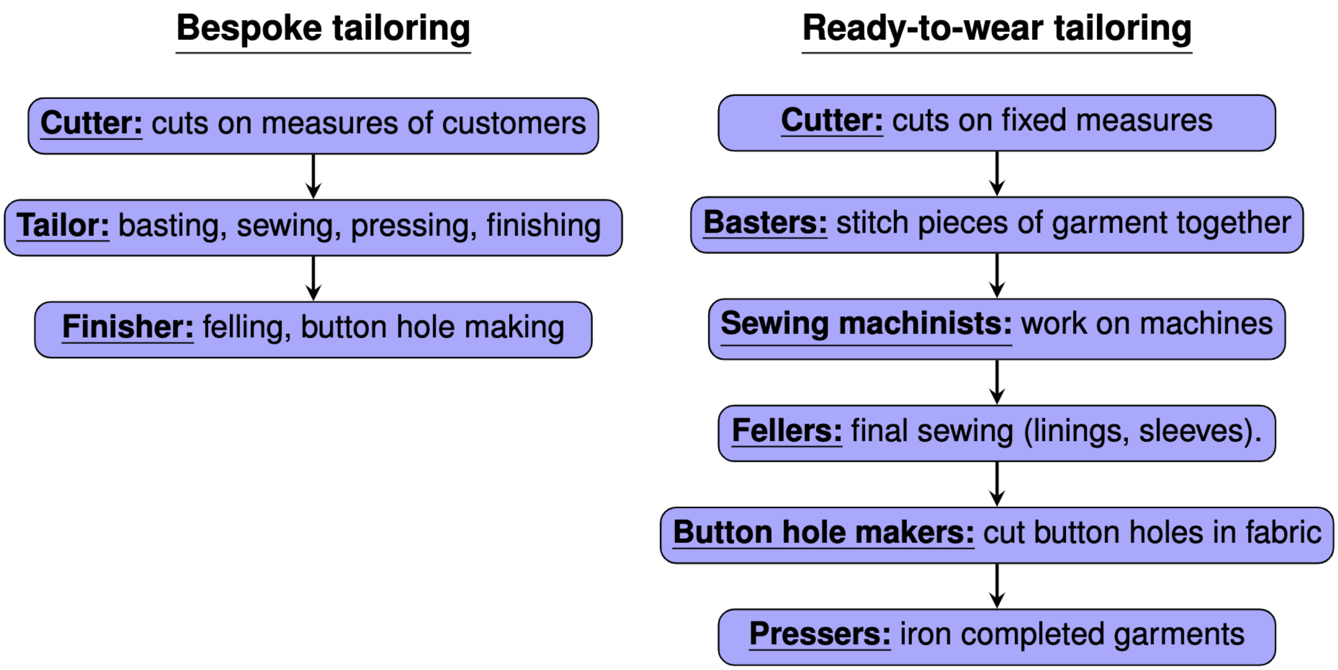
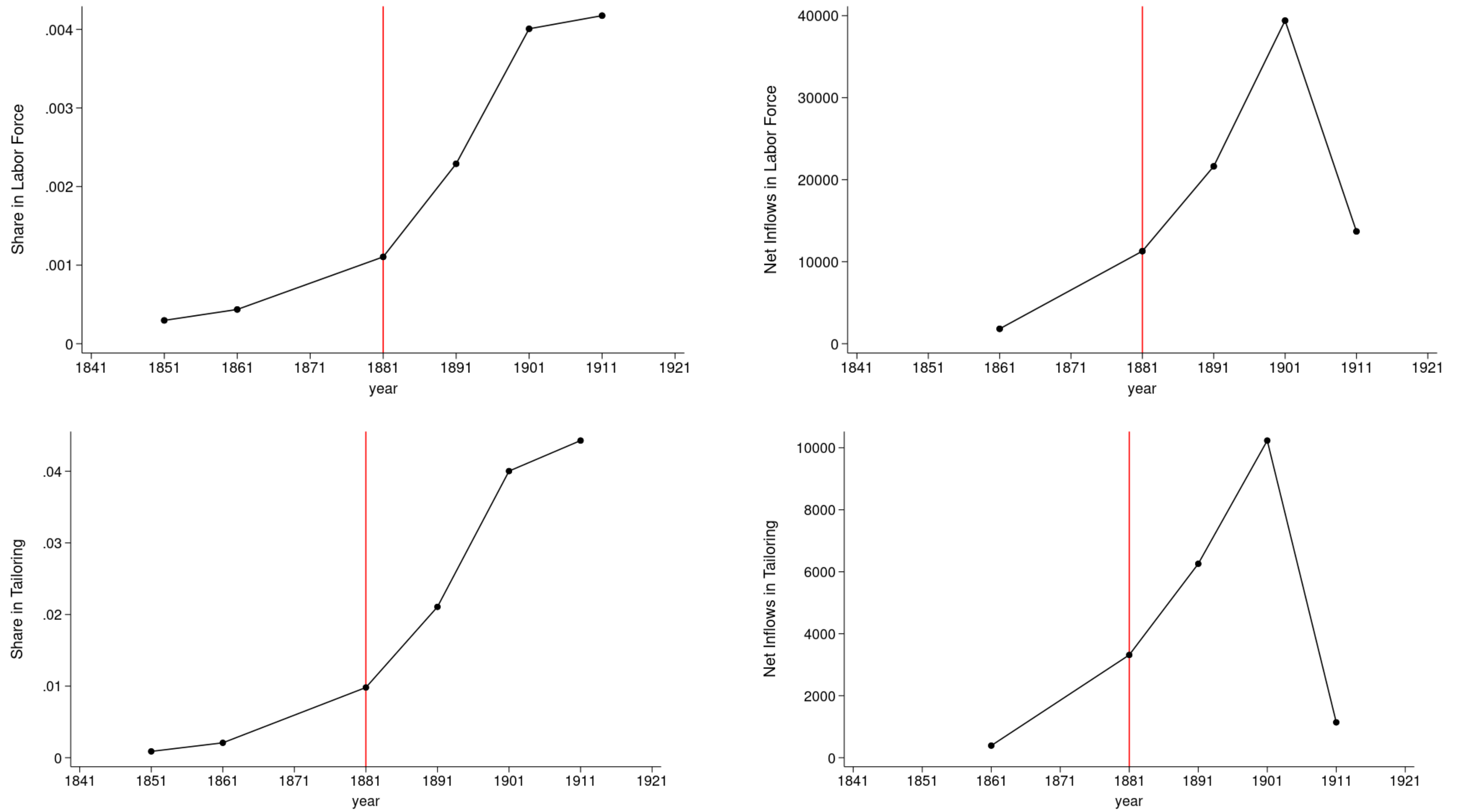
8 FIGURES

Figure 1: Production processes in bespoke and ready-to-wear tailoring



Notes: The figure illustrates the production processes in bespoke and ready-to-wear tailoring, as those are described in the Dictionary of Occupational Terms in Great Britain (1921). Production starts at the top of the diagram. The bespoke process is illustrated on the left and the ready-to-wear process is illustrated on the right.

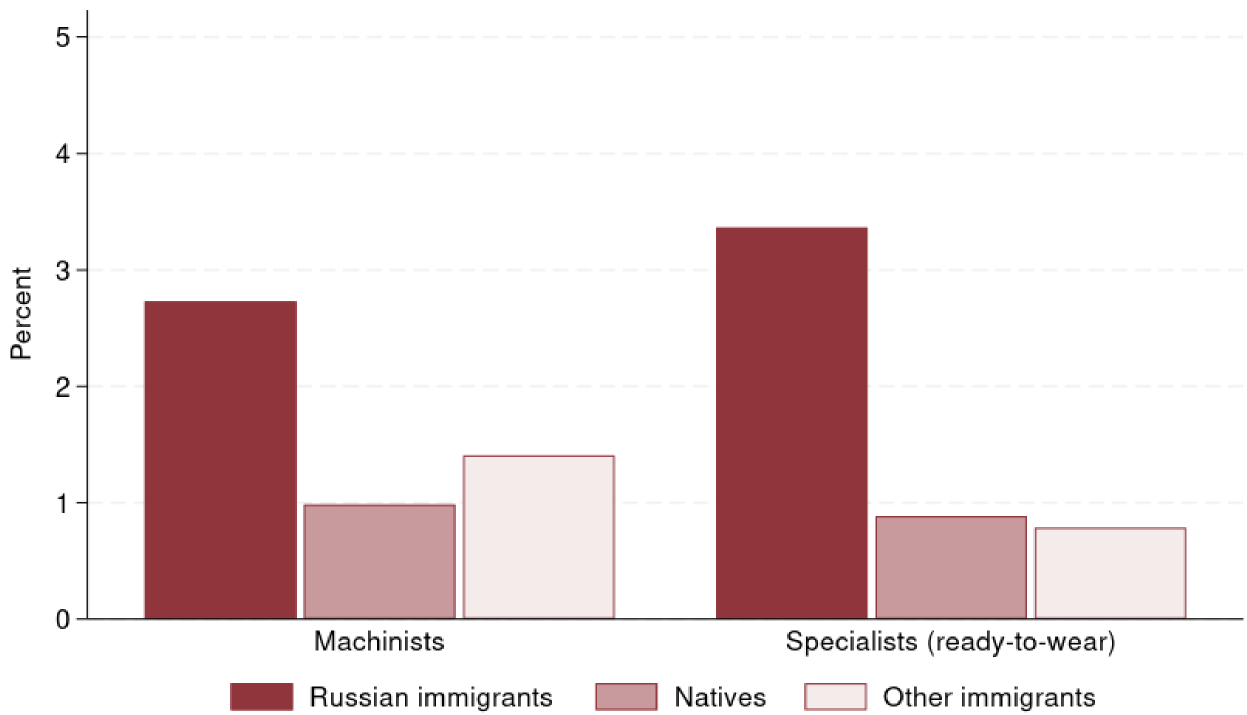
Figure 2: Shares and net inflows of Russian immigrants in the labor force and the tailoring industry



Source: I-CeM data (1851-1911).

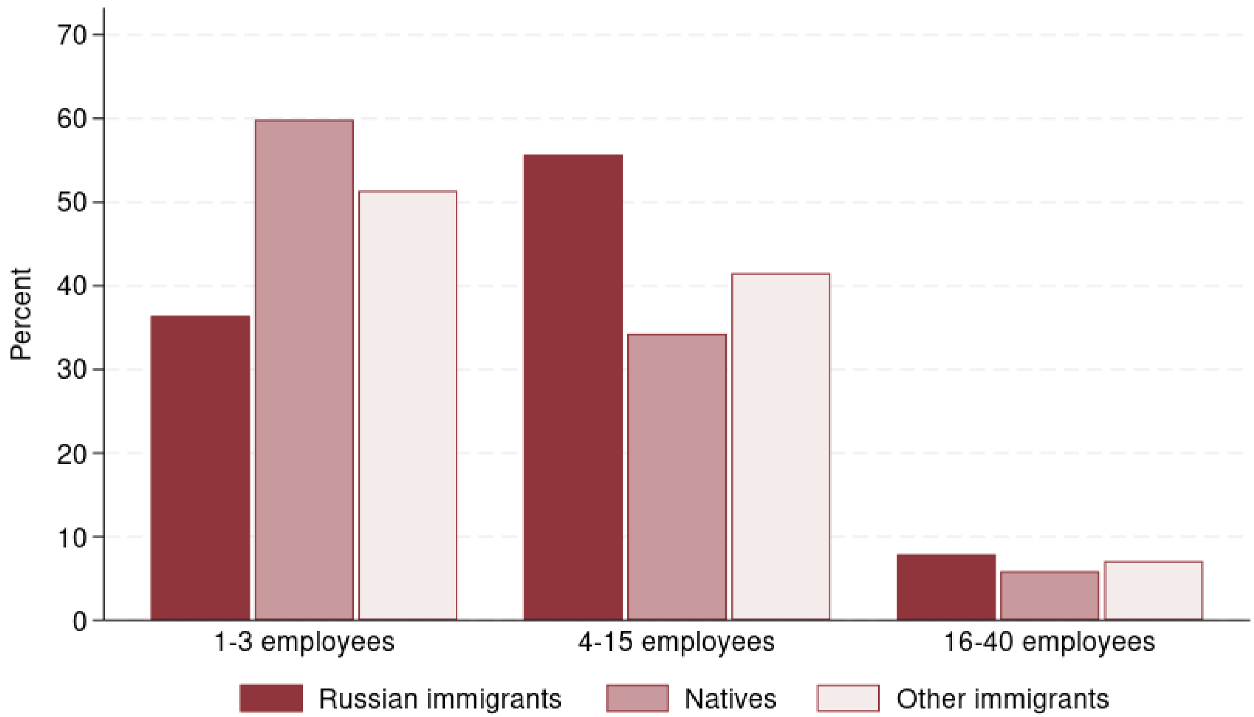
Notes: The top-left graph on this figure plots the share of immigrants born in the Russian Empire among the labor force (aged 15-65) in England. The bottom-left graph illustrates the same share within the workforce in the tailoring industry. The top-right graph depicts net inflows of these immigrants into the labor force, while the bottom-right graph shows inflows into tailoring. We identify an immigrant born in the Russian Empire as an individual born in today's Russia, Latvia, Lithuania, Poland, Belarus, Moldova or Ukraine (Pale of Settlement). We exclude from analysis individuals on British ships in home ports, in the royal navy whether at sea or abroad, on ships at sea or abroad and those on the military abroad.

Figure 3: Shares of machinists and specialists within groups of tailoring workers in 1881



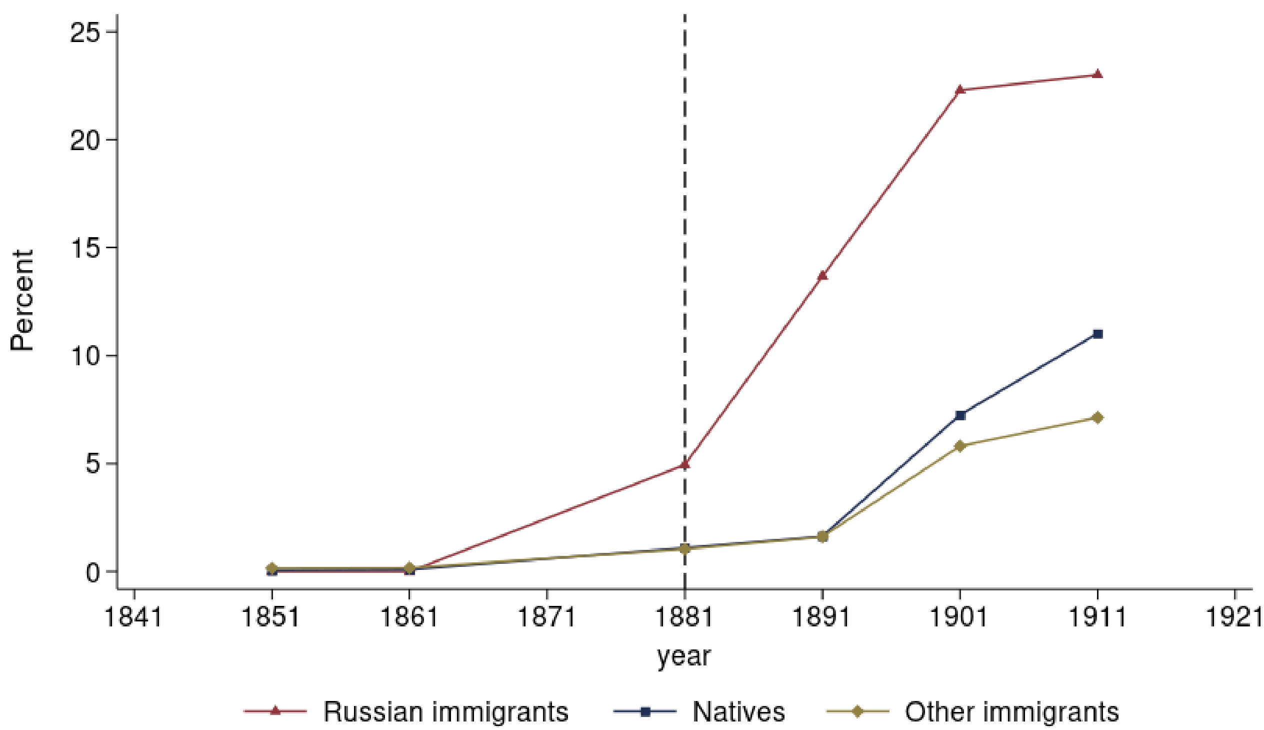
Source: I-CeM data 1881.
Notes: The figure uses our variable of micro-occupations to compare the shares of machinists and specialists among Russian immigrant tailors with those of native and other immigrant tailors in 1881.

Figure 4: Size of tailoring workshop in 1881 by group of owners



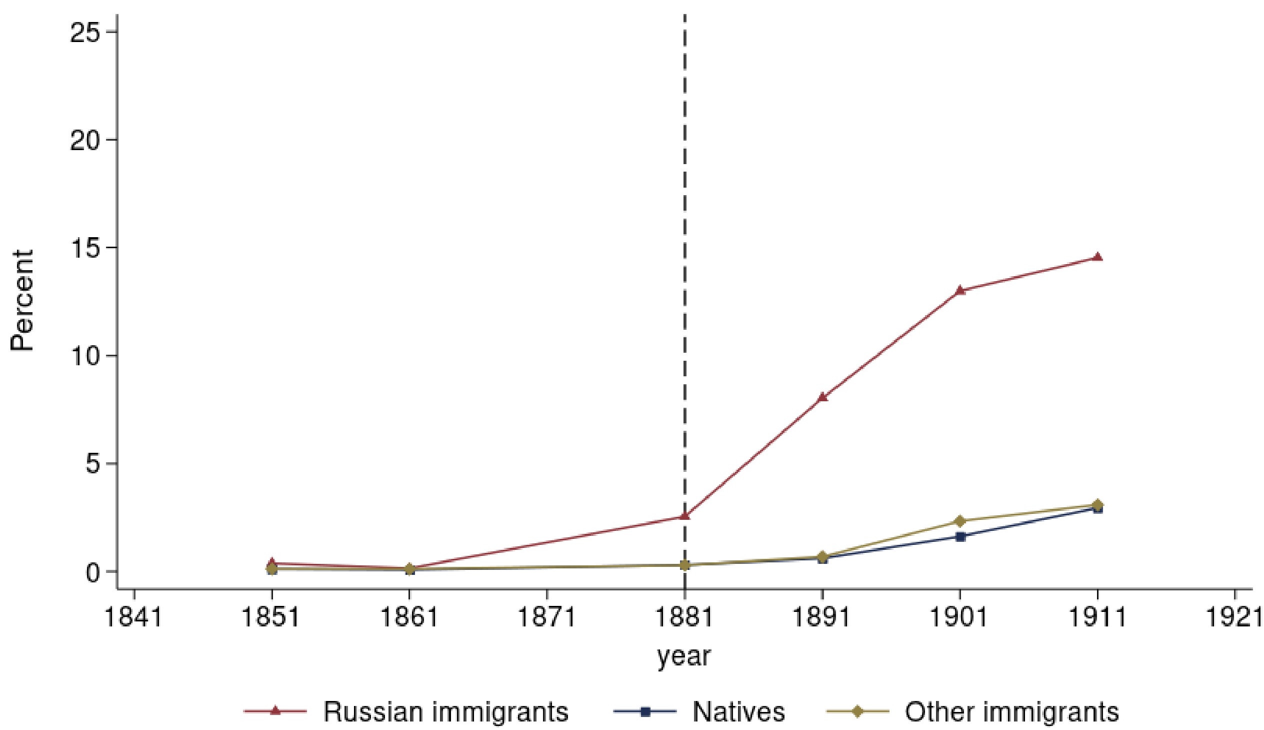
Source: BBCE data 1881.
Notes: The figure uses direct information on the number of employees working for each employer and compares the shares of Russian tailoring owners across three categories of workshop size relative to those of native and other immigrant owners. To focus on workshops we consider only employers with 40 employees or less. The three categories of workshop size are: those with 1-3 employees, those with 4-15 employees, and those with 16-40 employees.

Figure 5: Share of machinists within groups of workers in tailoring



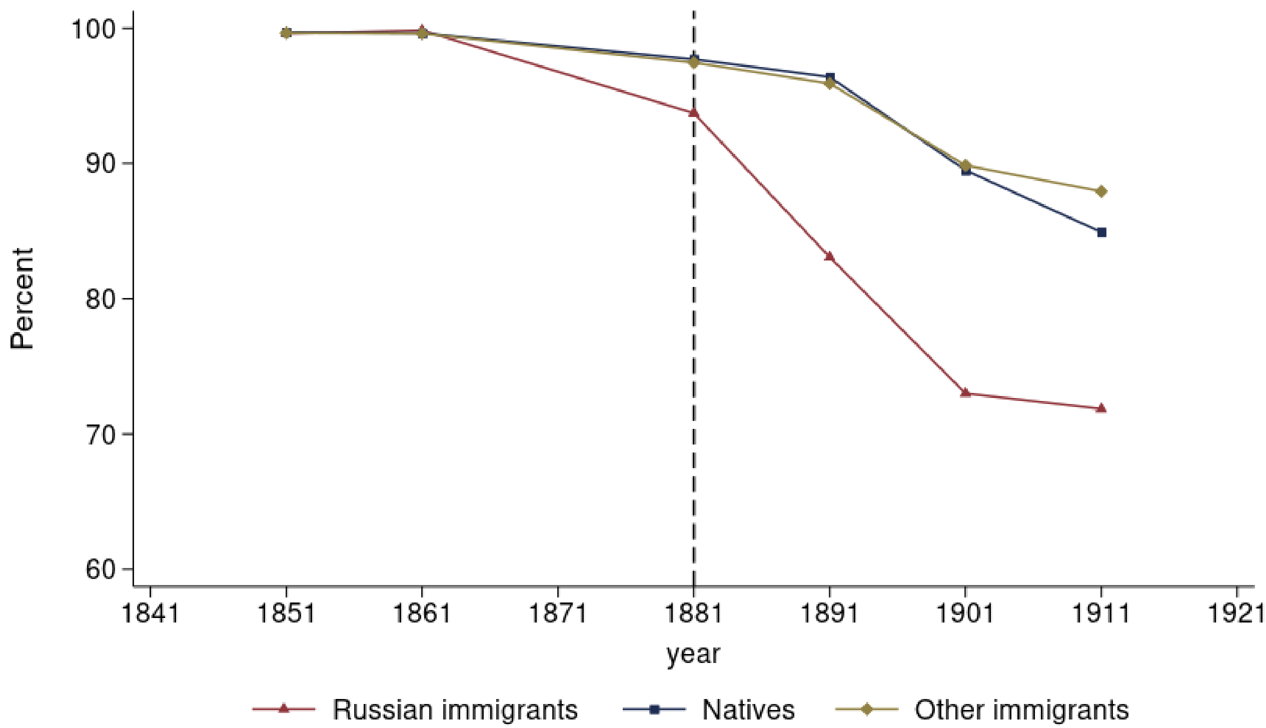
Source: I-CeM data 1851-1911.
Notes: The figure presents the evolution of the share of machinists among Russian immigrants, natives and other immigrant workers in tailoring.

Figure 6: Share of specialists within groups of workers in tailoring



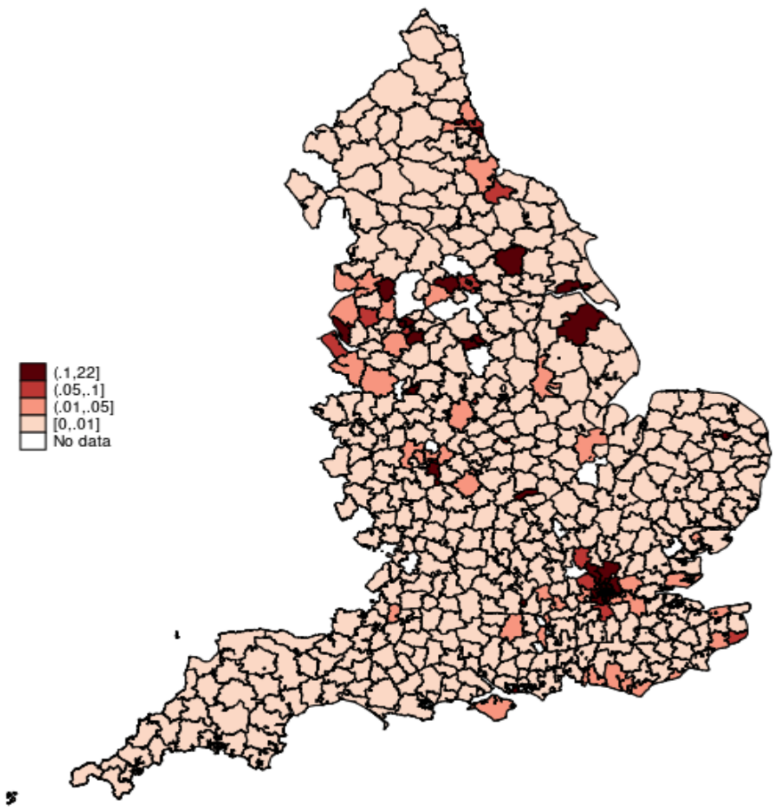
Source: I-CeM data 1851-1911.
Notes: The figure presents the evolution of the share of specialists among Russian immigrants, natives and other immigrant workers in tailoring.

Figure 7: Share of generalists within groups of workers in tailoring



Source: I-CeM data (1851-1911).
Notes: The figure presents the evolution of the share of generalists among Russian immigrants, natives and other immigrant workers in tailoring.

Figure 8: Inflow of Russian tailoring workers across districts in England 1881-1901



Whitechapel	20%
St. George East	17%
Stepney	16%
Leeds	12%
Manchester	7%
Westminster	4%
Bethnal Green	3%
Liverpool	3%
Kensington	1%
Birmingham	1%

Source: I-CeM data (1881-1901).
Notes: The map presents the distribution of the inflow of Russian tailoring workers across districts in England between 1881 and 1901. The table on the right lists the districts that absorbed the ten largest shares of the immigration influx.

9 TABLES

Table 1: Example Data

Industry Code	Original Census Response	New Variable	Country of Birth
653 (tailor)	tailoring presser	presser	Russian Empire
653 (tailor)	tailoring sewing machinist	machinist	Russian Empire
653 (tailor)	tailoring button hole	button holer	England
653 (tailor)	tailor's baster	baster	Russian Empire
653 (tailor)	tailoring	tailor	England

Notes: The table provides an example of our dataset, including the new variable of (micro-) occupations that we created.

Table 2: Occupation of Russian immigrants prior to arrival in England

Occupational distribution in country of origin: 1896-1901 arrivals	Percent
Agriculture	1.33
Manufacturing	70.26
Clothing	40.09
Tailoring	26.15
Other clothing	13.94
Wood and construction	13.65
Food	6.01
Metals	4.84
Other manufacturing	5.67
Commerce	23.04
Labourers and domestic services	0.22
Professionals	3.07
Other	1.51
Observations	23,560

Source: Poor Jews' Temporary Shelter in London Database 1896-1901.

Notes: This table presents the occupational profile of Russian immigrants that arrived in the shelter between 1896 and 1901, according to occupation in the country of origin as recorded in the shelter's records. The sample of consists of 23,560 records in which occupation was recorded, representing approximately 55% of the overall Russian immigrant inflow in England between 1891 and 1901.

Table 3: First stage results

	1881-1891 (1)	1891-1901 (2)
Shift-share, 1851 Russian tailoring shares	0.002^{***}	0.002^{***}
	(0.0001)	(0.0001)
Observations	554	554
R^2	0.4365	0.3410
F-stat	379.28	435.95

Notes: This table presents results from district-level regressions of the decennial change in the share of Russian workers in tailoring on the shift-share instrument constructed with the cross-district shares of Russian tailoring workers in 1851. Columns (1) and (2) show results for the decades 1881-1891 and 1891-1901 respectively. The change in the average age of workers in the district is included as a control. Robust standard errors are clustered at the district level and reported in parentheses. Significance: 10%(*), 5%(**) and 1%(***).

Table 4: The impact on the adoption of the sewing machine

	1881-1891				1891-1901			
	OLS	OLS	IV	IV	OLS	OLS	IV	IV
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PANEL A. Dependent variable: ΔShare of machinists in tailoring								
ΔShare Russian immigrants in tailoring	0.158***	0.158***	0.214***	0.214***	0.248***	0.248***	0.249***	0.249***
	(0.036)	(0.036)	(0.016)	(0.016)	(0.015)	(0.015)	(0.012)	(0.012)
Controls	no	yes	no	yes	no	yes	no	yes
R^2	0.2840	0.2840			0.2041	0.2041		
First-stage F-stat				379.28				435.95
Observations	554	554	554	554	554	554	554	554
PANEL B. Dependent variable: ΔShare of Russian immigrant machinists in tailoring								
ΔShare Russian immigrants in tailoring	0.124***	0.124***	0.166***	0.166***	0.196***	0.196***	0.197***	0.197***
	(0.028)	(0.028)	(0.007)	(0.007)	(0.009)	(0.009)	(0.009)	(0.009)
Controls	no	yes	no	yes	no	yes	no	yes
R^2	0.8812	0.8813			0.9589	0.9589		
First-stage F-stat				379.28				435.95
Observations	554	554	554	554	554	554	554	554
PANEL C. Dependent variable: ΔShare of native machinists in tailoring								
ΔShare Russian immigrants in tailoring	0.034***	0.034***	0.048***	0.048***	0.051**	0.051**	0.053**	0.053**
	(0.009)	(0.009)	(0.003)	(0.004)	(0.018)	(0.018)	(0.016)	(0.016)
Controls	no	yes	no	yes	no	yes	no	yes
R^2	0.0188	0.0188			0.0110	0.0110		
First-stage F-stat				379.28				435.95
Observations	554	554	554	554	554	554	554	554

Notes: Panel A presents results from regressions of the decennial change in the share of machinists on the change in the share of Russian- over native workers in tailoring. Panels B and C present results for the same regression with the changes in the share of Russian and native machinists in the outcome variable respectively. Regressions exploit variation across 554 districts in England with the change in the average age of workers in the district included as control. Std. errors are clustered at the district level. Significance: 10%(*),5%(**), 1%(***).

Table 5: Inflows of Russian specialists and generalists in tailoring

	1881-1891				1891-1901			
	OLS	OLS	IV	IV	OLS	OLS	IV	IV
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PANEL A. Dependent variable: ΔShare of Russian specialists in tailoring								
ΔShare Russian immigrants in tailoring	0.120***	0.120***	0.172***	0.172***	0.224***	0.224***	0.221***	0.221***
	(0.034)	(0.034)	(0.006)	(0.006)	(0.011)	(0.011)	(0.007)	(0.007)
Controls	no	yes	no	yes	no	yes	no	yes
R^2	0.8281	0.8281			0.9647	0.9647		
First-stage F-stat				379.28				435.95
Observations	554	554	554	554	554	554	554	554
PANEL B. Dependent variable: ΔShare of Russian generalists in tailoring								
ΔShare Russian immigrants in tailoring	0.753***	0.753***	0.656***	0.656***	0.577***	0.577***	0.581***	0.581***
	(0.063)	(0.063)	(0.014)	(0.014)	(0.020)	(0.020)	(0.016)	(0.016)
Controls	no	yes	no	yes	no	yes	no	yes
R^2	0.9821	0.9821			0.9801	0.9801		
First-stage F-stat				379.28				435.95
Observations	554	554	554	554	554	554	554	554

Notes: Panel A presents results from regressions of the decennial change in the share of Russian specialists on the change in the share of Russian over native workers in tailoring. Panel B presents results for the same regression with the change in the share of Russian generalists in the outcome variable respectively. Regressions exploit variation across 554 districts in England with the change in the average age of workers in the district included as control. Std. errors are clustered at the district level. Significance: 10%(*),5%(**), 1%(***).

Table 6: Impact on adoption of RTW by native tailors (specialists vs generalists)

PANEL A. Dependent variable: ΔShare of native specialists in tailoring

	1881-1891				1891-1901			
Independent variable	OLS (1)	OLS (2)	IV (3)	IV (4)	OLS (5)	OLS (6)	IV (7)	IV (8)
ΔShare Russian immigrants in tailoring	0.046^{***}	0.046^{***}	0.054^{***}	0.054^{***}	0.042^{***}	0.042^{***}	0.050^{***}	0.050^{***}
	(0.008)	(0.008)	(0.004)	(0.004)	(0.011)	(0.011)	(0.004)	(0.004)
Controls	no	yes	no	yes	no	yes	no	yes
R^2	0.0391	0.0392			0.0462	0.0462		
First-stage F-stat				379.28				435.95
Observations	554	554	554	554	554	554	554	554

PANEL B. Dependent variable: ΔShare of native generalists in tailoring

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔShare Russian immigrants in tailoring	-0.091^{***}	-0.091^{***}	-0.105^{***}	-0.105^{***}	-0.093^{***}	-0.093^{***}	-0.109^{***}	-0.109^{***}
	(0.016)	(0.016)	(0.007)	(0.007)	(0.030)	(0.030)	(0.020)	(0.020)
Controls	no	yes	no	yes	no	yes	no	yes
R^2	0.0481	0.0482			0.0222	0.0222		
First-stage F-stat				379.28				435.95
Observations	554	554	554	554	554	554	554	554

Notes: Panel A presents results from regressions of the decennial change in the share of native specialists on the change in the share of Russian over native workers in tailoring. Panel B presents results for the same regression with the changes in the share of native generalists in the outcome variable respectively. Regressions exploit variation across 554 districts in England with the change in the average age of workers in the district included as control. Std. errors are clustered at the district level. Significance: 10%(*),5%(**), 1%(***).

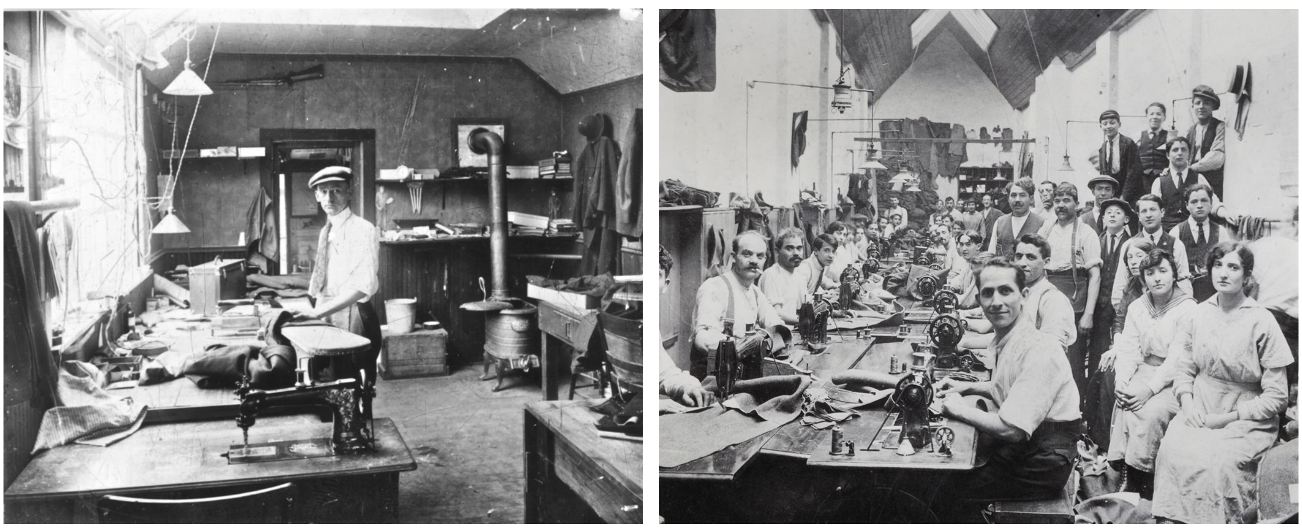
Table 7: The impact on the size of native tailoring firm

	1881-1891				1891-1901			
	OLS	OLS	IV	IV	OLS	OLS	IV	IV
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PANEL A. Dependent variable: ΔShare of native employees in tailoring								
ΔShare Russian immigrants in tailoring	0.154***	0.153***	0.151***	0.149***	0.100***	0.101***	0.144**	0.145**
	(0.032)	(0.032)	(0.055)	(0.055)	(0.029)	(0.030)	(0.058)	(0.058)
Controls	no	yes	no	yes	no	yes	no	yes
R^2	0.0039	0.0042			0.0099	0.0121		
First-stage F-stat				379.28				435.95
Observations	554	554	554	554	554	554	554	554
PANEL B. Dependent variable: ΔShare of native employers in tailoring								
ΔShare Russian immigrants in tailoring	0.003	0.003	0.024*	0.024*	0.016*	0.016*	0.011	0.011
	(0.007)	(0.007)	(0.013)	(0.013)	(0.006)	(0.006)	(0.010)	(0.010)
Controls	no	yes	no	yes	no	yes	no	yes
R^2	0.0000	0.0001			0.0025	0.0025		
First-stage F-stat				379.28				435.95
Observations	554	554	554	554	554	554	554	554
PANEL C. Dependent variable: ΔShare of native self-employed in tailoring								
ΔShare Russian immigrants in tailoring	−0.156***	−0.156***	−0.175***	−0.174***	−0.116***	−0.117***	−0.155**	−0.156**
	(0.030)	(0.030)	(0.063)	(0.063)	(0.033)	(0.033)	(0.066)	(0.066)
Controls	no	yes	no	yes	no	yes	no	yes
R^2	0.0044	0.0047			0.0120	0.0141		
First-stage F-stat				379.28				435.95
Observations	554	554	554	554	554	554	554	554

Notes: Panel A presents results from regressions of the decennial change in the share of native employees on the change in the share of Russian over native workers in tailoring. Panels B and C present results for the same regression with the changes in the share of native employers and self-employed in the outcome variable respectively. Regressions exploit variation across 554 districts in England with the change in the average age of workers in the district included as control. Std. errors are clustered at the district level. Significance: 10%(*),5%(**), 1%(***).

A Appendix Figures

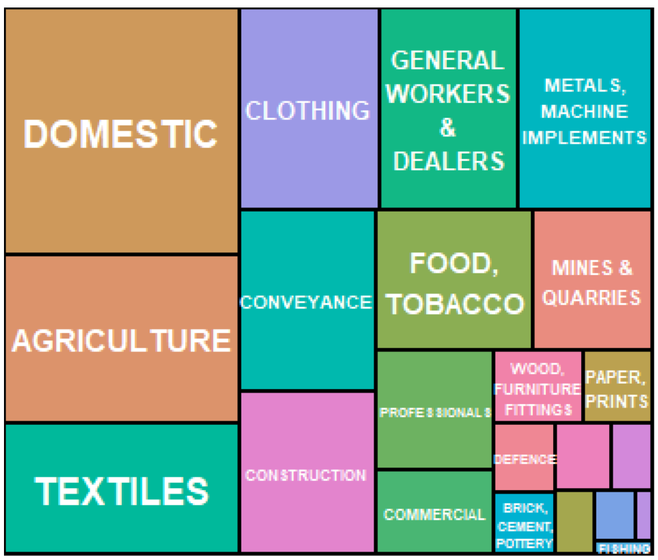
Figure A1: Pictures of workshops of native and Jewish immigrant tailors in England



Workshop of native tailor Workshop of Jewish immigrant tailor

Notes: The picture on the left illustrates a workshop of a native tailor. The picture on the right illustrates the workshop of Jewish immigrant tailor established at the East End of London.

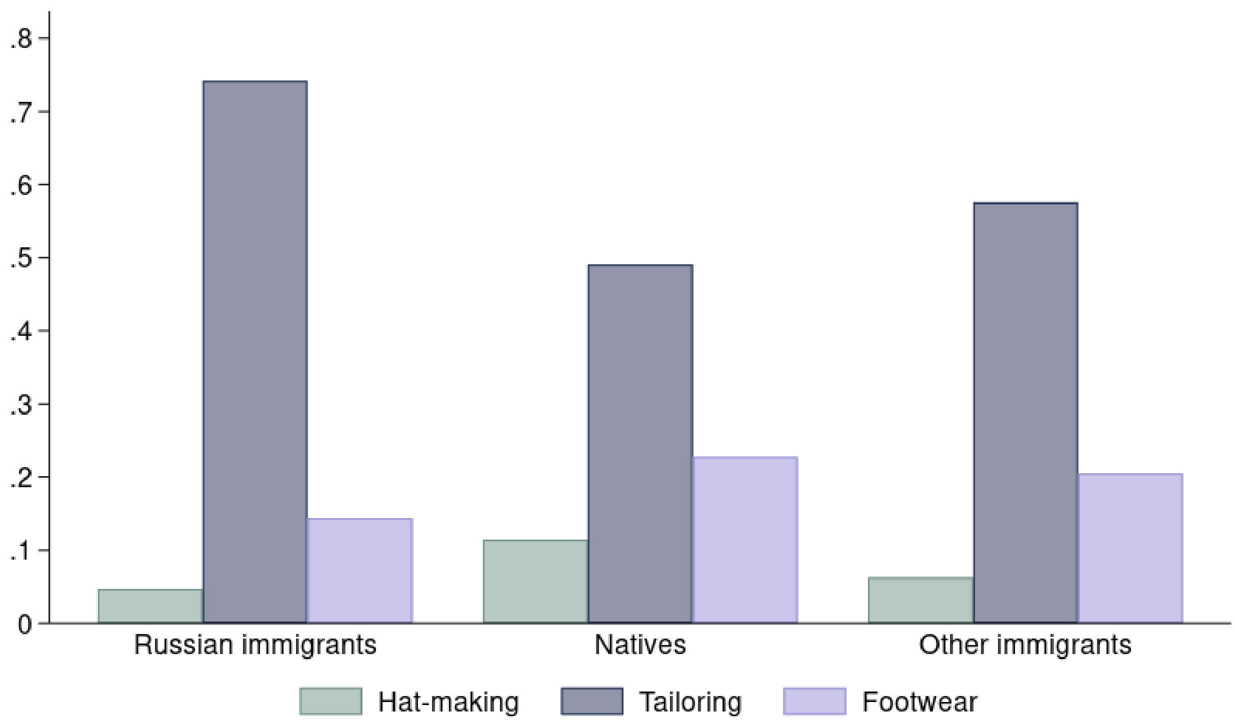
Figure A2: Employment Distribution by Sector in England in 1881



Source: I-CeM data 1881.

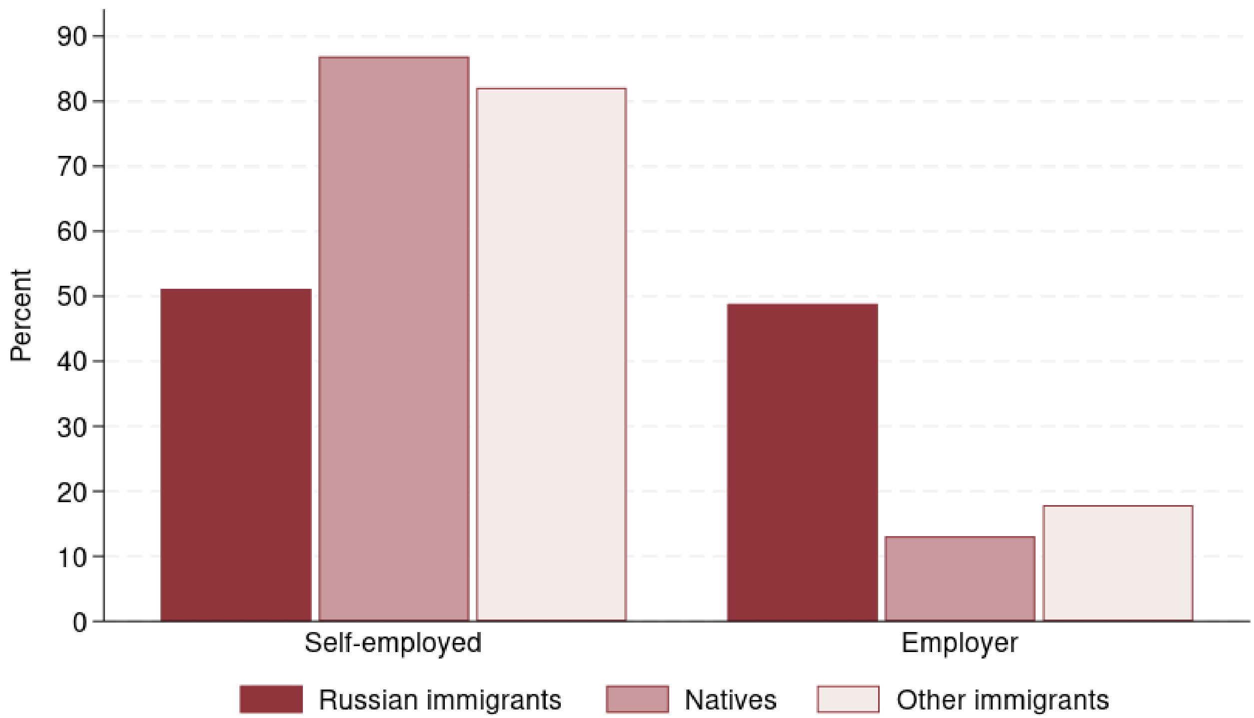
Notes: The tree map illustrates the distribution of employment across sectors in England in 1881. The clothing sector was the fourth largest sector of employment account for 8% of the total workforce in this year.

Figure A3: Industrial distribution by group of clothing workers in 1881



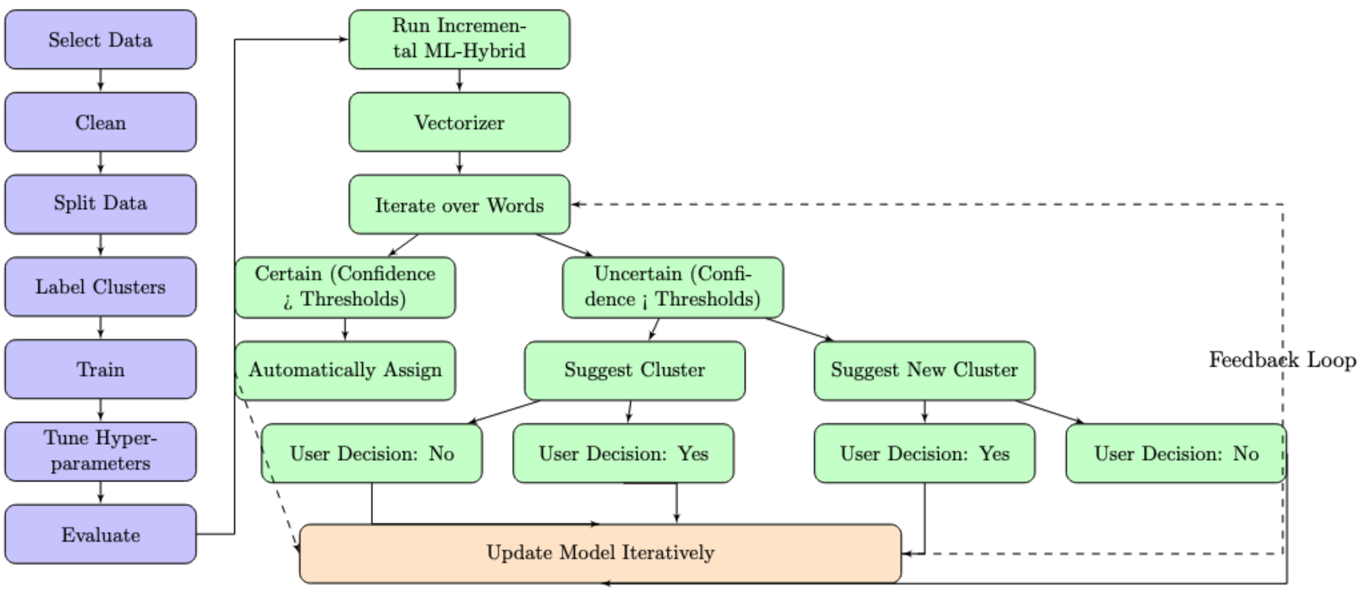
Source: I-CeM data 1881.
Notes: The figure illustrates the distribution of Russian immigrants across different industries within the clothing sector, comparing their representation to that of native and other immigrant clothing workers in England in 1881.

Figure A4: Self-employment by group of tailoring entrepreneurs in 1881



Source: BBCE data 1881.
Notes: The figure compares the proportions of Russian tailoring entrepreneurs who are self-employed to those who act as employers. It contrasts these shares with those of native and other immigrant tailors in England in 1881.

Figure A5: Incremental Machine Learing



B Appendix Tables

Table B1: First stage with location of native tailors in 1851 as instrument

	1881-1891 (1)	1891-1901 (2)
Shift-share, 1851 native tailoring shares	-0.512^{**} (0.248)	-0.765^{**} (0.347)
Observations	554	554
R^2	0.0002	0.0007
F-stat	2.37	2.50

Notes: This table presents results from district-level regressions of the decennial change in the share of Russian workers in tailoring on the shift-share instrument constructed with the cross-district shares of native tailoring workers in 1851. Columns (1) and (2) show results for the decades 1881-1891 and 1891-1901 respectively. The change in the average age of workers in the district is included as a control. Robust standard errors are clustered at the district level and reported in parentheses. Significance: 10%(*), 5%(**) and 1%(***).

Table B2: Location of Russian tailoring workers and wealth in 1851

Dependent variable: Share of Russian tailoring workers concentrated in district

Wealth indicator	(1)	(2)	(3)	(4)
Share bottom 10% social status in district's population	0.0002	-0.0001		
	(0.00011)	(0.00003)		
Share top 10% social status in district's population			0.0005	0.0012
			(0.00031)	(0.00077)
Controls	no	yes	no	yes
R^2	0.0054	0.0137	0.0382	0.0590
F-stat	2.04	1.45	2.41	1.31
Observations	554	554	554	554

C Constructing Granular Information on Occupation: "Tasks"

Every British census taken between 1851 and 1911 asked individuals to provide descriptions of their occupations. William Farr, the superintendent of the statistical department at the General Register Office (GRO) in the United Kingdom at the time, indicated that the responses given by citizens should capture five key aspects of their work: "skill, talent, or intelligence; tools, instruments, machinery or structures; materials; processes; products".[13] Indeed, these aspects are often reflected in the responses householders provided. The descriptions given varied significantly, ranging from one-word summaries to more detailed responses with 10-15 words.

The Integrated Census Microdata project (ICeM) has digitized the original English Census data for the decades between 1851-1911, excluding census year 1871. The new ICeM dataset makes individual level census observations digitally available for the first time (Higgs and Schurer, 2020), and has substantially expanded the frontiers of research on British occupational structure over the second half of the 19th century. However, when the ICeM project digitized the data, they retained the pre-existing, industry level, categorization of occupation. This left the more granular data on occupation sealed in the strings describing occupation. Our approach to extracting the "tasks" from the strings is twofold. First, we make use of a straightforward deterministic approach. Second, we employ an incremental machine learning approach, as illustrated in the figure below. Both approaches have been previously used to construct tasks for the boot-making industry in Victorian Britain (Vipond, 2022).

C.1 Deterministic Approach

The process of constructing the "task-level" classification proceeds in three steps: all unique strings describing occupation for Tailors are collected, then tokenized, and a set of categories is constructed from the most frequent "task" terms.

First, we collect the complete set of tailors in England across all census years. Second, we determine the main set of tasks present in the unique strings. We employ a filtration process to

[13] Census(1861): general report

subset to the “tasks” which occur most frequently in the strings. The first part of the filtration leverages Zipf’s Law, the highly skewed distribution of the strings. We extract the “task” words available in those strings. These are now identified categories of “tasks” in tailoring. The remaining unique character strings, those not accounted for by the initial sweep, are then extracted and tokenized. The frequencies of individual words are tallied. “Task” words found to be most frequent are added to the set of tailor “tasks”.

Finally, once the categories - or types of task - have been discovered, the character strings in the “occupation” are parsed and assigned to the new “task” categories. The topic modelling process results in the construction of a dictionary, with topic categories assigned to keywords and their spelling variations. From this point, assigning strings to task categories based on the presence of the keywords in the string is straightforward. For example, in Table 1, the third observation includes the keyword ”machinist”, so this person will be assigned to the category machinist. It should be noted that the “task” level could be dis-aggregated further. For example, all “cutters” are collected into one category, irrespective of what type of material they cut. Likewise, no distinction is made regarding what material is used in the tailoring process.

C.2 Machine Learning Approach

The process is illustrated in Appendix Figure A5. It begins with a traditional machine learning pipeline. Data is selected and cleaned, and then split into training and test sets. Again, Zipf’s law is leveraged. The most frequent set of strings is extracted, tokenized, and clustered. Clusters are on the basis of tasks. A model is then trained on the labeled clusters, and performance fine-tuned through hyper-parameter optimization. The model’s accuracy is evaluated on the test data.

Following this, the workflow transitions into an Incremental Learning Hybrid phase, where the model is continuously refined. In this phase, a vectorizer processes new incoming data. The model iterates over individual tokens, classifying them based on its confidence levels. When the model is highly confident, it automatically assigns labels. For uncertain cases, it suggests potential clusters and incorporates feedback from the user, either confirming or rejecting these suggestions. Over time, the model is updated iteratively, incorporating both automatic classifications and user feedback, which helps it improve and adapt to new patterns in the data. This iterative feedback loop ensures that the model's performance improves progressively as more data is processed.

We take this human-in-the-loop incremental learning approach to classification for two main rea- sons. Firstly, while the straightforward deterministic model employed for bootmakers and tailors is effective, it does not scale efficiently. This limitation becomes apparent as we extend our analysis to Task data across all industries. The machine learning approach scales. To ensure accuracy, we use the results from the manual deterministic approach as a ground truth for additional validation. Secondly, we find existing topic modeling methods, which often require setting a number of predefined categories, inadequate. The incremental machine learning allows me to generate categories flexibly, and incorporate knowledge of the occupational structure of the period. In practice, it is essentially supervised learning over multiple iterations.