Technological Unemployment in Victorian Britain -
Young Workers and the Collapse of Entry

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Abstract

We do not know whether technological unemployment swept across England in the wake of the British Industrial Revolution. In this paper, I propose an approach to quantify jobs lost to, and created by, creative destruction in the 19th century. Using over 170 million individual records from the full-count British census (1851–1911), I generate sub-industry "task" level occupational data. I apply this to the English bootmaking industry as it mechanized. The new data reveal sharp structural changes: 152,000 artisanal jobs disappeared as skills became obsolete, while 144,000 new jobs emerged. However, incumbent bootmakers were rarely displaced. Instead, the decline was driven by young men no longer entering the artisanal trade. These findings challenge assumptions about displacement, showing how slow adoption and persistent demand can shield existing workers, while opportunities vanish for new entrants.

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Introduction

Did technological unemployment sweep across England in the wake of the British Industrial Revolution? We do not know. The extent to which the new machines replaced workers, leaving them temporarily unemployed, has never been quantified. Some scholars refer to the technological unemployment which caused devastating short-term harm to workers during the Industrial Revolution (Landes, 2003; Frey, 2019), while others doubt the scale of the impact (Mokyr et al., 2015). This lack of agreement reflects the paucity of data available on labour displacement and reinstatement in Victorian Britain.

Two decades of research on skills-biased technological change has provided considerable evidence that the impact of new technologies on occupational structure and wage is best viewed at the "task" level of occupation (Acemoglu and Autor, 2011). I therefore create a new, more finely grained occupational categorization structure, using text recorded in individual-level English census observations, as digitized by the Integrated Census Microdata project (ICeM), as data. This allows me to quantify - for the first time - the number of jobs lost, and created, over the latter half of the 19th century.

For three centuries sustained economic growth has been powered by the invention and adoption of new technologies. These innovations have made jobs obsolete, and displaced workers. Simultaneously, they have generated new employment opportunities. The two outcomes have been modelled as countervailing forces, with jobs created offsetting jobs lost (Acemoglu and Restrepo, 2019). Research on the future of work has investigated which workers are most likely to be exposed to labour displacement driven by the adoption of new technology (Frey and Osborne, 2017), and the individual consequences of occupational decline (Edin et al., 2019). A long-run view of the impacts of occupational decline would contribute an additional dimension to the debate. However, data on labour displacement in historical contexts rarely exists. This paper proposes an approach which reveals and quantifies technological unemployment in England between 1851-1911, and thereby opens the door to research on the intergenerational impacts of labour displacement.

Labour displacing technologies have been the norm since the British Industrial Revolution, and a hallmark of modern economic growth. Lamplighters in New York lost their jobs to electricity in the early 1900s (Frey, 2019), and tens of thousands of American women lost their jobs as telephone operators in the 1920s (Feigenbaum and Gross, 2020). In the present day, nearly 2 million American truck drivers risk unemployment if their industry is automated. A much discussed paper has estimated that up to 47% of jobs in America are at risk of automation in the next few decades (Frey and Osborne, 2017). Yet, for all that the parade of new technologies has displaced labour, making skills and jobs obsolete, it has simultaneously generated new jobs, and created demand for entirely new skillsets. This "reinstatement" of labour has, up to the present day, outpaced labour displacement. An early attempt to quantify the emergence of new jobs estimated that 8.5% of American workers in 1980 were employed in occupations which did not exist in 1965 (Lin, 2011). Building on this work, new research estimates that more than half of the jobs which currently employ Americans did not exist prior to 1940 (Autor, 2022; Autor et al., 2022).

With the fourth industrial revolution on the horizon, long-standing anxieties about the impacts of new technologies on the future of work have resurfaced. Two key questions are at stake. The first is whether new technologies will continue to be able to create jobs at the rate they displace them. There are scholars who believe that recent developments in AI herald the end of this era, with AI now out-competing human labour on multiple fronts (Susskind, 2020). The second is whether the cyclical waves of technological adoption tilt access to opportunity, as some segments of the labour market capture the newly generated job opportunities, and other groups are left behind. The asymmetrical impacts of creative destruction on demand for labour are being studied. Research on who is most at risk of technological unemployment is extensive. To date, there is agreement that those working in routine jobs (Bank, 2018; Autor et al., 2022), and older workers (Autor and Dorn, 2009) are most at risk. A much smaller body of literature considers the individual consequences of occupational decline (Edin et al., 2019; Braxton and Taska, 2023; Acemoglu and Restrepo, 2022).

History is well placed to offer insight into how consecutive waves of technological adoption impacted access to opportunity in the labour market. It should grant a wide-angle lens on the question, and be able to consider whether the consequences of the shocks ripple through generations. However, labour displacement in historical contexts has seldom been quantified, and this is a prerequisite to investigating these questions. The existing literature consists of a handful of studies. This includes new research from Feigenbaum and Gross (2020), which explores the impacts of the mechanization of the telephone industry in the United States. They find that incumbents were pushed out of the labor market or into lower-paying jobs. However, they also learn that the mechanization of this particular industry did not have a deleterious impact on opportunities for future generations of young women, as new employment in other sectors became available to fill the gap. Other papers have taken a more comprehensive, but less direct, approach to the question. Kogan et al. (2021) draw on nearly two centuries of patent data, match it with administrative data, and find that technological innovation in the United States has been correlated with declining wages and fewer employment opportunities for incumbents in impacted industries. Atack et al. (2019) makes use of the Hand and Machine Labour Study, commissioned in the United States in 1894, to discover the relative cost and productivity of hand and machine labour. They find that mechanization in various industries led to both job loss and job creation.

However, this constitutes a small number of studies for what may have been a watershed moment in labour displacement history. Even in Great Britain, which was the first country to industrialize, and where the events of the Industrial Revolution have been scrutinized, the impact of mechanization on labour displacement has not been well explored. Certainly, British workers at the time were concerned that the new technologies would lead to labour displacement: there is narrative evidence of this from the Luddite uprisings, from the Swing Riots, and in the hive of union activity arising from technological anxiety. Leading intellectuals of the time – Karl Marx and David Ricardo, amongst others - were alarmed. However, we do not know if labour displacement swept across England in the wake of the unprecedented adoption of the new technologies. Scholars hold radically diverging views. David Landes, for instance, claims that the adoption of the new technologies "...destroyed the livelihood of some and left others to vegetate in the backwaters of the stream of progress...the victims of the Industrial Revolution were numbered in the hundreds of thousands or even millions" (Landes, 2003), while others doubt whether this took place at all (Mokyr et al., 2015). This profound difference of opinion is viable only because there is so little data to bring to bear on the question.

This paper proposes a solution which allows job loss and job creation in 19th century England to be quantified. I propose a tasks-based approach, which uncovers the impact of the adoption of new technologies in 19th century Britain on the occupational structure. It is informed by research on routine biased technological change (RBTC), which has found that the impact of new technologies on wage premiums is often visible at the "task" level of occupation (Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2019; Autor, 2022; Autor et al., 2022). In RBTC models wage penalties reflect weakened demand for certain types of labour, as demand shifts in response to the adoption of new technologies. While weakening demand for labour can drive wages down, a collapse in demand can result not only in decreasing wages, but in job losses in the industry and, eventually, in occupational decline - there are so few gas lamplighters in the United States in the 21st century because there is so little demand for them. A tasks based approach to identifying job loss and job creation has seldom been used, even with modern data, because individual level data on occupation is rarely available at the task level.

At present, 19th century English census data tracks occupation at the industry level. This masks and obscures shifts in the occupational structure taking place at more granular levels. By moving to a tasks based approach the transformations to the occupational structure taking place at a sub-industry level can be revealed. I develop a new, "task" level categorization structure, using text recorded in individual level English census observations, as digitized by the Integrated Census Microdata project (ICeM) (Schurer et al., 2022), as data. I apply this new approach to assessing the impact of mechanization on one industry, English Bootmaking.

The bootmaking industry was large, employing approximately 220,000 people, nearly a fifth of whom were women. This makes for a total of 1.3 million observations of individuals working in the bootmaking industry over the six English census returns taken between 1851-1911. Mechanization was precipitated by the introduction of the sewing machine in 1858, and continued through to the early 20th century. I assign 1.29 million observations of English bootmakers, or 97% of the total population of bootmakers during the period, to the sub-industry level "tasks" they performed.

Analysis at this level reveals that approximately 152,000 jobs were lost in England and Wales as the new technologies rendered skills obsolete, while another 144,000 jobs, demanding new skills, were created. Incumbent bootmakers were not able to keep up with the shifting demands of the industry. They did not transition out of obsolete "tasks" and into the newly generated ones. Instead, the new opportunities went to young people, particularly those born in the geographical locations in which the new jobs were emerging.

This new, "task-based", approach to occupation opens the door to quantifying technological unemployment across all industries in Great Britain over the latter half of the 19th century. It is a stepping stone to research exploring the welfare consequences of technological unemployment over the long-run. It is worth noting that, as a term, technological unemployment has largely been retired from the lexicon. Popularized by John Maynard Keynes in the 1930s (Keynes, 1930), it tends to refer to permanent technological unemployment, which occurs only when no new jobs are generated to offset those lost to creative destruction. A less specific term, "labour displacement", has now been widely adopted to describe the temporary unemployment which emerges from cycles of creative destruction, and has the advantage of not evoking connotations of permanent technological unemployment. However, since both unemployment and technology are salient elements of the process being discussed, the term "transitional technological unemployment" has the advantage of being more accurate.

The paper is organised as follows. Section 1 reviews the historical setting for the mechanization of the English Bootmaking industry. Section 2 introduces the data, and the construction of the key variables, including the task-level occupational classification, family structure, and linked panel datasets. Section 3 presents the new evidence revealed by taking a task-level approach, revealing how the occupational structure changes in tandem with the onset of mechanization.

It presents the scale and pace of these changes. Section 4 presents the empirical strategy, Section 5 provides results, and Section 6 concludes.

1 Historical Context

Bootmaking was the single largest craft industry in 19th century Britain, and the fifth most important occupation.[1] Bootmakers made up 2.9% of the working population in England in 1851. It was an industry responsible for directly employing nearly a quarter of a million people, a fifth of whom were women. Indirectly, it provided a household income for just over a million people, a substantial share of the 18 million individuals who lived in England in 1851. Boots have always been desirable products in the context of British weather, and in times of war the government invested heavily. The Napoleonic Wars, for example, provided a major boost to the industry.[2]

The mechanisation of the English Bootmaking industry was precipitated by the introduction of the bootmaking sewing machine in 1858, and evolved through the second half of the 19th century. This period coincides with the window for which high quality individual-level census data is available. Since the census returns include individual level information on occupation, it is possible to explore the impact of mechanization on workers in the bootmaking industry.

A comprehensive narrative treatment of the evolution of the bootmaking industry in England does not exist, although several papers consider earlier periods, in the 18th century (Riello, 2002), and on changes in the bootmaking industry in the first half of the 19th century (Church, 1970). Additionally, there is a rich literature on the evolution of the industry at the county level (Hatley and Rajczonek, 1971; Greenfield, 1998; Mounfield, 1965), and a small collection of articles which treat with the process of mechanization in Britain (Church, 1968; Menuge, 2001).

In contrast, the history of the American Bootmaking industry has been well documented, and can inform an understanding of the British case. The first task of bootmaking to be mechanised

[1]In order, the largest industries are: domestic workers, agriculture, general labourers, coal mining, bootmakers, and dressmakers.

[2]In 1857 it was estimated that each man in the army required 2 pairs of boots a year. Select Committee on Public Contracts, B.P.P. 1857, 11, 661 (Church, 1970).

was in “binding”: the sewing together of the leather pieces which form the upper part of the shoe. The sewing machine, patented by the American Elias Howe in 1846, was modified in 1852 to be able to do the heavy work of sewing together boot leather (Thomson, 1989). The second task of bootmaking to be mechanised was in “finishing”: affixing the sole of boot to the leather “uppers”. The Blake Sole sewing machine represented the first breakthrough in this area, in the 1860s. Several years later, the innovation of the first Goodyear welt machine was introduced, in 1872, and by the 1880s an improved version dominated this process (Thorn, 1987). The final category of bootmaking tasks, “clicking”, or cutting out the leathers of the upper part of the shoes, was highly skilled, and was not mechanised until later in the 20th century.

Many of the breakthrough innovations in the shoemaking industry were developed by workers, and the invention of a sewing machine suitable for bootmaking was no exception. A foreman in the shop of a major shoemaking concern in Lynn, Massachusetts, had recognised the potential of applying the Singer sewing machine to the work of bootmaking, and made the required modifications. The sewing machine had been labour saving – a shirt that had taken a skilled tailor 14 hours to sew by hand could be assembled in one hour on the machine, and it was clear there was similar potential in bootmaking. This turned out to be the case: once the boot-leather sewing machines were developed, workers with the machine could produce more than four times a worker without the machine. Estimates from the Hand and Machine Labour study in the United States indicate that mechanization was responsible for an 80% savings in labour input as the bootmaking industry transitioned from craft to machine production (Atack et al., 2019).

In the United States, the introduction of the sewing machine to bootmaking had three key impacts. Firstly, it was labour saving, and resulted in technological labour displacement. Secondly, it proved pivotal in catalysing the further mechanisation of the bootmaking industry. Finally, it drove the shift from craft to factory production. Technological unemployment in the particular task of “binding” was an immediate result of this innovation. It was a task which almost exclusively employed women, and, in Lynn - one of the main shoemaking production cities in Massachusetts - the employment of women fell from 6500 to 3900 between 1850-1860 following the introduction of the bootmaking sewing machine. This is a small sample, geographically limited, but illustrative of the labour displacing impacts of the new machine. The labour displacement has been attributed to the machine introducing a temporary mismatch between productivity in binding the uppers and in the other tasks that made up the process of assembling shoes: the ratio of people needed for each task in the assembly of boot making changed, resulting in unemployment in the task which had been made more efficient (Thomson, 1989). That bottleneck then resulted in the second impact of the sewing machine: an incentive to mechanize the next task as rapidly as possible. By the end of the 1870s every conceivable task of bootmaking was being mechanised. The sewing machine not only precipitated a cascade of further innovation, it also drove the shift from cottage industry to factory production (Thomson, 1989).

The mechanisation of the boot making industry in England followed a similar trajectory. An important difference, however, can be found in resistance from organised labour. The rapid adoption and integration of the machine in the United States stands in stark contrast to the reception it had in much of the rest of the world, where the process was more fraught, as tailors and bootmakers worried that the machine would make their labour obsolete. Indeed, one of the reasons that the sewing machine is an American invention at all is the result of labour resistance. The first functioning sewing machine was invented in France, by M. Thimonnier, in 1830, a full two decades before the American sewing machine began to establish itself. He was able to patent his machine, and secure financial backing. He then managed to win a contract with the military. However, 200 local tailors rioted, and burned down his workshop, with its 80 wooden, flammable, sewing machines. He was not able to recover, and the machine had to wait for its American inventors to take its place on the world stage.

English manufacturers made an attempt to introduce the American bootmaking sewing machines in 1855. They faced effective and concerted resistance from organised labour, and were delayed. Nonetheless, in 1857 the first of these machines were imported and set to work. In Northamptonshire and Staffordshire, two well established centres of bootmaking in England, there was uproar. A letter from a manufacturer in Northampton, who introduced one of the first machines in 1857, declares that he was immediately met by a deputation of bootmakers who demanded that he get rid of the machine, and that when he did not do so, there followed a strike lasting 15-18 months, in which the workers "swore that they would drive [him] and [his] machine out of town altogether". His letter is dated 1865, and he notes with some satisfaction that the workers were not able to achieve either objective, and that more than 1500 machines are now at work in the town.[3] This might not have matched the response produced in Ireland, where an oversized replica of the machine was smuggled into a local theatrical performance, with the intention of infuriating striking tailors, and where the owner engaged in a formal boxing match with tailors outside the theatre itself, but it was considerably more robust. Rather than a few bouts of angry exchange, the adoption of the machine in England sparked a two year strike, from 1857-1859, with 2000 men from Northamptonshire and Staffordshire out on the tramp (Thorn, 1987).

Nonetheless, by the 1860s the sewing machine revolution was well underway across the United Kingdom. Starting with sales of a few thousand machines per year in the early 1860s, extremely rapid uptake resulted in sales of nearly 50,000 machines per year only a decade later. By the 1890s around 150,000 sewing machines of all types were being sold in England every year. In total, a minimum of 4.3 million sewing machines, designed for all types of textile work, would have been sold in the UK between 1865-1911 (Godley, 1996). The shock-waves were those of the adoption of a new general purpose technology. To understand the impact of this technological shock on labour displacement and reinstatement in the English Bootmaking industry I turn to occupational data recorded in the British census.

2 Data

Every British census between 1851 and 1911 asked individuals to describe their occupation. William Farr, the superintendent of the statistical department at the General Register Office (GRO) at the time, advised that the description of occupation was meant to reflect five key aspects of work: "skill, talent, or intelligence; tools, instruments, machinery or structures; materials; processes; products" [4], and indeed these elements of the work are often present in the

[3]See Appendix A for more detail on this process.
[4]Census (1861): General Report

responses householders provided to the occupation question. The responses given ranged from parsimonious one-word summaries through to detailed descriptions. See the variable for "Occupation", given in Table 1, below, for an example.

Table 1: Occupations in 19th-century English census data

Year	Occupation	Occode	HISCO	Task
1851	CORDWAINER	663	80100	Cordwainer
1851	BOOT AND SHOE MAKER - MASTER EMPLOYING 4 MEN 4 WOMEN and 5 APPS	663	80100	Maker
1851	BOOT AND SHOE BINDER	663	80100	Binder
1851	BOOT AND SHOE RIVETTER	663	80100	Riveter

Note: Individual-level observations. First three columns as in ICeM digitized data. Final column shows the newly constructed task variable derived by the author.

When the GRO received the census enumerators' books for the decennial census taken in 1851, the records contained hundreds of thousands of unique character strings describing occupation. For the bootmaking industry alone there were more than 60 000 unique descriptions. The GRO realized that managing the data at this level of granularity was untenable, and devised a taxonomy of approximately 800 industries. Clerks employed by the GRO were responsible for assigning each individual observation to the correct industry, and analysis based on English and Welsh census data has predominantly been conducted at the industry level of occupation from that point onwards.

The Integrated Census Microdata project (ICeM) has recently 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 (Schurer et al., 2022), 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 encrypted the more granular information on occupation which has been available – if all but hermetically sealed into the text by the constraints of processing big data - for nearly 200 years.

2.1 Micro-occupation: "task" classification

I construct a sub-industry level “task” classification scheme by extracting information from the original textual description of employment. An example of this is given above in Table 1: the final column contains the new “task” variable, which indicates the type of work the individual did within their industry. The process of constructing this “task-level” classification proceeds in three steps: all unique strings describing occupation are collected, tokenized, and a set of categories is constructed from the most frequent “task” terms.

Firstly, I collect the complete set of bootmakers in England across all census years.[5] There are approximately 200,000 bootmakers observed in each decennial census for England, resulting in a total of ~1.3 million individual level observations. I then extract all the unique textual descriptions of occupation in this industry: there are 60,137 unique strings. There are fewer unique strings than individual level observations, because unique strings are found multiple times. For example, the description “Cordwainer” is given for thousands of individual observations, whereas the character string “Boot & Shoe Maker (Master Employing 4 Men 4 Women & 5 Apps)” occurs only once in the census records.

The second step is to determine the main set of tasks present in the unique strings. This is a topic discovery process, approached both with and without machine learning.[6] I employ a filtration process to 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. I extract the “task” words available in those strings. These are now identified categories of bootmaker “tasks”. 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 bootmaker “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 modeling process

[5]See Appendix B for more detail on this process.
[6]see Appendix C for further detail

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 ”Binder”, so this person will be assigned to the micro-occupational "task" of binder. It should be noted that the “task” level could be disaggregated further. For example, all “Cutters” are collected into one category, irrespective of what type of material they cut. Likewise, the category of “Binders” includes all those who do binding work, irrespective of whether this is for slippers, boots, shoes, or whether it takes place in a hospital or any other environment.

It is certainly the case that some descriptions of occupation contain more than one keyword. However, these are rare. In the bootmaking industry, of 1.29 million individual observations, 51,000 (3.8%) contain two or more keywords. When several keywords exist within one description of occupation, the assignment of the observation to a category is based on a pre-established hierarchy of keywords. This can be conceptualized as a matrix of word pairs, in which the ranking of each keyword, vis-a-vis all the others, is given. For example, if the keyword “machinist” is set at the top of the hierarchy, this means that any individual who describes their occupation as both “machinist” and “shoemaker” will be assigned to the “machinist” group. Were I to put “machinist” at the bottom of the hierarchy of keywords then all other keywords would be given priority, and the individual would be assigned to the “machinist” task only if the description contained no other keywords. The hierarchy of keywords used, together with sensitivity checks on the impacts of using a different hierarchy, is available in Appendix D. The hierarchy is set to maximize granular information. The least specific occupational descriptions, for example “Shoemaker”, “Worker”, “Hand”, are at the bottom of the hierarchy. If there is any other keyword present in the text description, the person will be assigned to that category. An individual who described their occupation as a “Riveter Shoemaker”, for example, is categorized as a riveter. The top of the hierarchy is given to keywords which reflect mechanization: a “Machinist Binder” will be registered as a machinist.

The final step in the process is to check that the set of keywords identified can allocate at least

95% of all individual level observations in each year to a sub-industry level “task”. This is done by merging the crosswalk back into the complete population data for English bootmakers, and checking what proportion of observations are not allocated to a “task” category. If the set of tasks does not cover at least 95% of strings in each year then an additional task category is added to the set from the frequency of tokenized words. The process is reiterated until the set of keywords is sufficient to meet the threshold. The process was devised with the intention of producing crosswalks for every industry in the census, to enable the construction of a “task” level variable across the entirety of the ICeM dataset.

2.2 Census Linking

I link cross-sectional decennial census records to create two longitudinal datasets. These are: "Panel 1": 1851-1861, and "Panel 2": 1861-1881. I link all employed individuals in Britain forward to the next time period, tallying around 10 million individuals.

Women are often dropped from longitudinal data constructed by record linking algorithms. This is because women routinely changed their surname when they married during this period, and it becomes challenging to follow individuals when they change their names. However, as I show in Vipond (2023B), marriage is a rare event in a woman’s life. Most women do not change their surname in any given decade. Many women are married and stay married, many women who are widowed do not re-marry, and some women stay single. Approximately 70% of women do not change their surname in a ten year period, and these women can therefore be linked by the same process which is used to construct longitudinal data for men. This does, however, mean that the longitudinal data excludes women who married and changed their name in the period. It is possible that labour market outcomes for these women might be meaningfully different than expected outcomes for other women, and we cannot therefore expect that the results which we see in the remainder of this paper apply to this group. However, in this particular case, the exclusion of newly married young women is likely to understate the magnitude of the results in this paper.

I follow my own approach to record linking. Please see Vipond (2023B) for a full explanation.

One of the key challenges in record linking with historical data is that the samples generated can vary substantially according to the choice of census linking model specification. Research making use of these constructed longitudinal datasets can result in findings which are simply driven by choice of census linking algorithms.

For example, Helgertz et al. (2022) show that approximately 50-75% of the individuals in the longitudinal dataset created by the ABE census linking algorithm report as "migrating" from their county or state of residence in the ten year period. In contrast, a high quality hand-linked sample shows only 7% of individuals migrating from their State, while 18% left their county of residence. These extremely different results highlight the impact false positives can make to outcomes of interest in the linked dataset. Social mobility, migration, and other outcomes of interest, are particularly vulnerable to this, depending on type of matching process used.

However, I find that British Historical Census Data, which can leverage granular time-invariant information on place of birth, is much less exposed to the false positives than equivalent American data would be. I demonstrate that the results in this paper are robust to a range of census linking model specifications, and I can therefore be certain that the findings are not being driven by the choice of census linking specification.

2.3 Family Units: Birth Order

To analyse intergenerational responses to technological change, I work extensively with the sons of bootmakers. I first reconstruct family units directly from the census returns using the individual's relationship-to-head variables, together with surname, household identifier, address, and parish. This allows me to identify households headed by a bootmaker and to collect all co-resident sons linked to that household head in each census year. For each identified family, I calculate the birth order of sons by ranking them by age within the household. This yields a consistent set of father–son dyads and a birth-order measure that can be used to examine selection into particular occupations and within-family patterns of labour market behaviour.

These reconstructed families have natural limitations. Older sons may have left home, meaning that the available family structure reflects only the children still living with their parents at the time of enumeration. Nevertheless, the resulting dataset captures the vast majority of bootmaker households and provides a rich framework for analysing the occupational choices of sons. The family links and birth-order information together allow me to study how opportunities shifted within families during the mechanization of the bootmaking industry.

3 New Evidence

The new, granular data on occupation reveals structural change that was invisible at the industry level of analysis. I find that approximately 152,000 old, artisanal bootmaking jobs disappeared as the industry mechanized, while 144,000 new, more specialized jobs emerged. At the national level, the countervailing forces of job loss and job creation nearly netted out in this particular case. However, that was not true at the regional level. The older, artisanal jobs disappeared in every English county following mechanization. However, the new, emerging jobs were very heavily concentrated in Northamptonshire and Leicestershire. The geography of the industry shifted, and became much more heavily concentrated.

3.1 Job Loss and Creation

Having classified the textual descriptions of occupation for the set of 1.3 million individual level observations of English bootmakers from 1851-1911 into “tasks”, it is now possible to assess the impact of mechanization on the occupational structure of the bootmaking industry at both the existing industry level of occupation and the newly available sub-industry task level. There are two key findings.

Firstly, the new "task" level analysis reveals labour displacement which is almost entirely masked at the industry level. An analysis of the impacts of mechanization on net employment in the bootmaking industry, conducted at the industry level, shows only a minimal shock. See Figure 1A, below. Prior to mechanization, in 1851, the English Bootmaking industry employed approximately 220,000 workers. Following a minor dip, it employed approximately 213,000 workers in 1911. At this level of analysis, any labour displacement which might have occurred is invisible.

The new “tasks” level analysis makes it possible to pry open this black box. Figure 1B and 1C show the evolution of “old” and “new” tasks in the English Bootmaking industry over time. Two things are immediately apparent. Firstly, job loss and creation did take place as the industry mechanized: the number of people employed in “old” bootmaking tasks declined by about 152,000, while 144,000 new jobs were generated in emerging work.

Secondly, it is sharply clear that increasing specialization accompanied mechanization. The category of “old” tasks is defined as including the five tasks which account for the employment of 95% of English Bootmakers prior to mechanization. In the decennial census data prior to the adoption of the new machines, 97% of bootmakers were employed as “Shoemakers”, ”Cordwainers”, ”Cloggers”, ”Binders”, ”Closers”. As mechanization set in, a rapid fragmentation of the occupational structure at sub-industry level took place. New types of employment emerged, including, but not limited to: sewing machinists, riveters, operators, and the foremen and managers who took up the new jobs in the factories. The intensification of specialization continued through to 1911. It may be appropriate to conceptualize this as a modern production process displacing an older, more traditional one.[7] Given that the findings in this paper hinge on the assertion that changes in these descriptions of occupation over time are not merely shifts in nomenclature, but reflect real differences in the kind of work done by individuals, please find evidence in support of this in Appendix E.

[7]Increasing specialization can be seen in that the set of 30 “tasks” account for a decreasing percentage of the individual observations in the data. In the 1851 census, the set accounts for 99% of bootmakers, by 1911, it accounts for 95%.

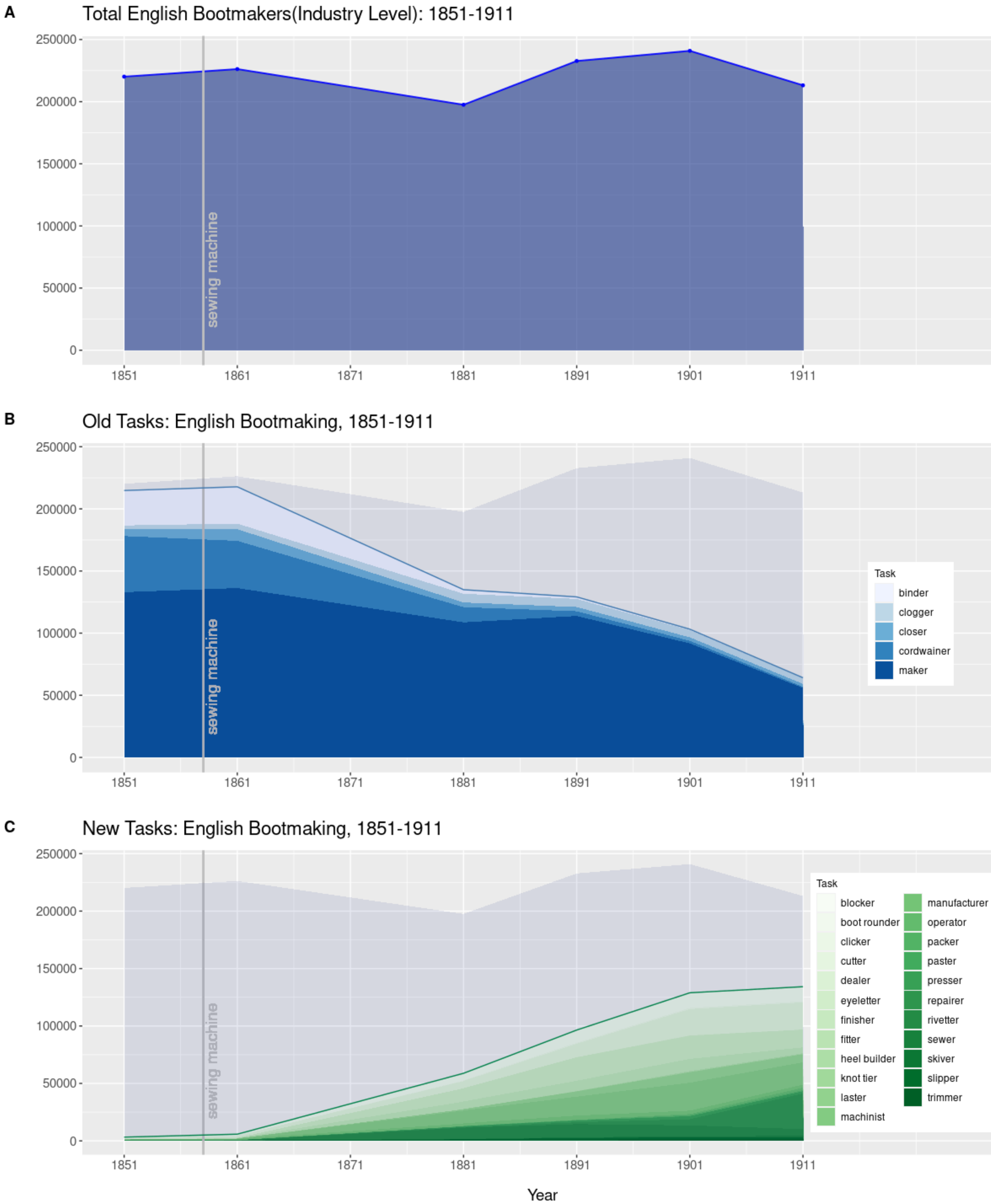


Figure 1: Number of Bootmakers Employed - Industry and Task Level, 1851-1911

Source: data derived by author from ICeM census records. Note: There is a 38% national collapse of artisanal jobs over the first 20 year window after the shock, between 1861-1881. Please see appendix F for detail on the rate of change. Observations for tasks with a sample size of less than 50 removed.

3.2 Geography

The task level analysis of the geography of employment reveals that the newly generated opportunities emerged in only a few counties, while the decline in employment in the "old" tasks took place in every county in England. Figure 2, below, illustrates the total change in the number of bootmakers employed in "new" and "old" tasks in each English county between 1851-1911.[8]

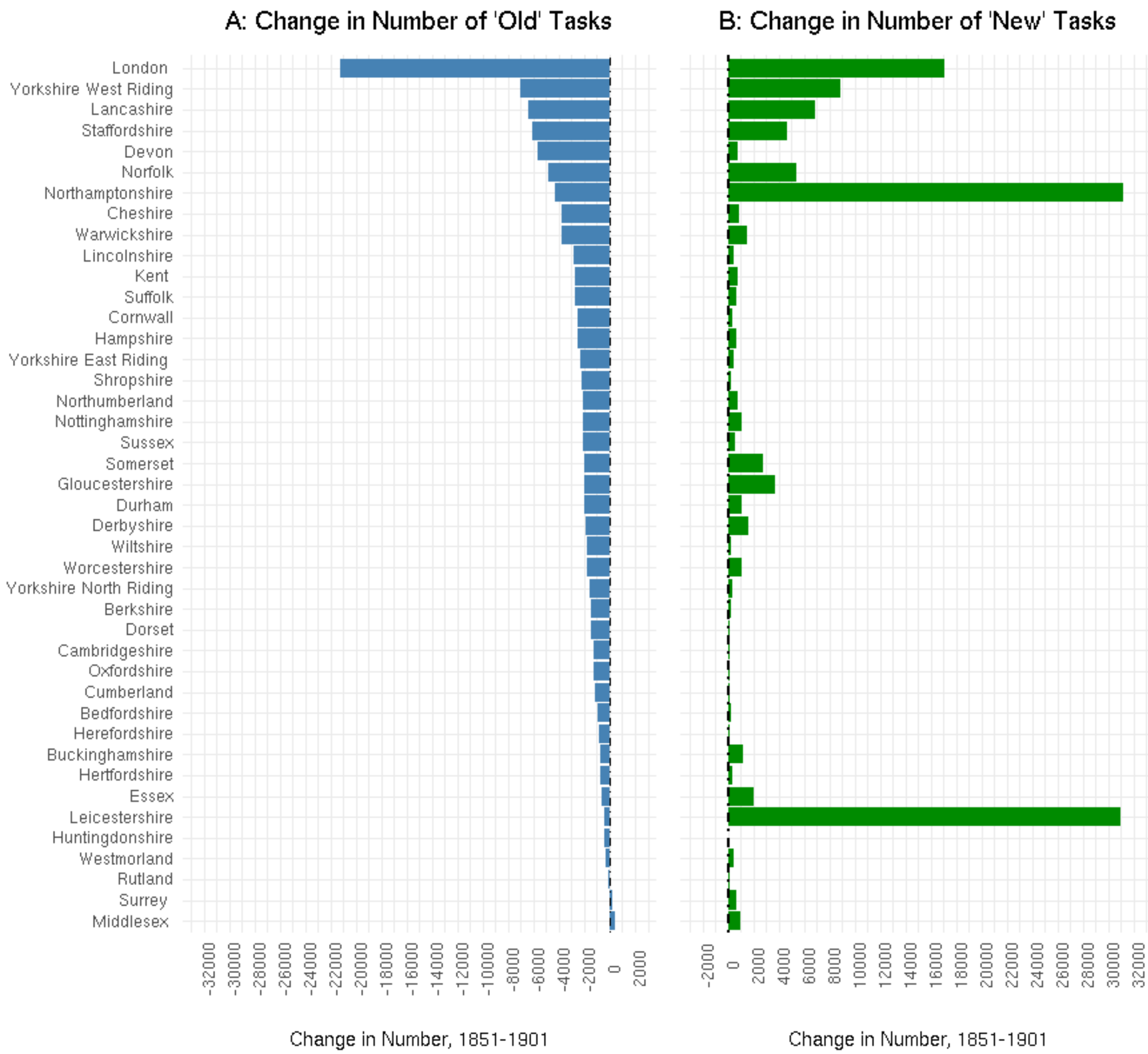


Figure 2: Change in Number of Bootmakers Employed in Old and New Tasks
Source: data derived by author from ICeM census records.

The overall picture is one in which the "older" and more general types of work declined ev-

[8]These categories are defined as they were when first introduced in the previous section.The old tasks are those which, together, were responsible for the employment of 97% of bootmakers in 1851 and 1861, prior to mechanization. These include: "binders", "cloggers", "closers", "makers", and "cordwainers".

erywhere, while employment opportunities in the "new" tasks emerged only in a select few counties. In the majority of English counties the loss of employment in the old tasks was not matched by the emergence of new opportunities, and the outcome was a net loss of workers employed in bootmaking. In a few English counties the loss of employment was matched by the emergence of employment opportunities in the new bootmaking tasks. In these counties there was no net change in the number of bootmakers employed in the industry. Finally, in two counties – Northamptonshire and Leicestershire – the loss of employment in the older, traditional tasks was more than compensated for by the surge of employment opportunities in the new kinds of work.

The net result of these countervailing forces of job loss and job creation, interpreted geographically, was a tectonic shift in the location of the industry. Northamptonshire and Leicestershire became enclaves of the English Bootmaking industry during this period, and the industry contracted substantially in other counties. Nearly half of the new jobs - 44% - were generated in Leicestershire and Northamptonshire alone.

The new types of work which emerged as the industry mechanized reflect a shift from craft to factory production. Many of the new jobs only existed in factories and larger enterprises: for example, foremen, supervisors, operators, factory workers, and some of the new sewing machinists. Since these new jobs emerged in only a few counties it seems that the shift to factory production in the bootmaking industry did not unfold uniformly across England, but instead primarily took place in only a few counties. The British Business Census of Entrepreneurs (BBCE) project identifies employers and proprietors between 1851-1911, and details how many workers were employed by each employer (Van Lieshout et al., 2021). Making use of BBCE data I find that large companies became increasingly concentrated in the counties in which the new kinds of work emerged: Leicestershire, Northamptonshire, and London.

4 Empirical Strategy

The new, granular data on occupation reveals previously invisible shifts in the occupational structure following mechanization. In the remainder of this paper, I focus on the disappearance of roughly 150,000 artisanal jobs in the bootmaking industry as it mechanized.

I start by asking who experienced this job loss. Given that these jobs disappeared, who bore the burden of this labour displacement? In principle, mechanization could have displaced existing artisans by pushing incumbents out of the trade, or by deterring new entrants, or both. Using linked census data which tracks individuals over time, I separately measure exit from artisanal bootmaking among incumbents, and entry into the trade among young men in each county. This allows me to distinguish whether the contraction in artisanal employment was driven by higher exit, lower entry, or a combination of the two.

I proceed in two steps. First, I estimate the displacement of incumbents and potential entrants using a difference-in-differences framework that compares bootmakers to workers in other industries within sex-specific labour markets. Having documented the adjustment margin, I then ask whether these changes were driven by the shock of mechanization, rather than shifting opportunities elsewhere in the economy.

4.1 Labour Displacement

The disappearance of artisanal bootmaking jobs implies that the contraction must have been absorbed on one of two margins: either incumbent artisans exited the trade, or young workers stopped entering it.

To determine which margin adjusted, I estimate the extent of labour displacement among incumbent bootmakers. If incumbents did not bear the brunt of the contraction, then the adjustment must have occurred through a decline in entry into artisanal bootmaking. I therefore separately examine changes in entry rates among young men across counties and cohorts.

I begin by examining the adjustment margin available to incumbent bootmakers. In principle, mechanization could have displaced existing artisans either by pushing them out of the bootmaking trade altogether, or by reallocating them into the new factory-based bootmaking jobs. The linked census data allow me to observe both outcomes directly. Incumbents very rarely moved into the new mechanized tasks within the bootmaking industry, and reallocation into factory work played almost no role in absorbing the shock. See Appendix G for evidence. The question of whether incumbent bootmakers experienced an increase in exit rates from the industry is somewhat more complex.

First, I focus on identifying whether mechanization drove incumbent artisans to exit the occupation at higher rates than comparable workers. To measure displacement, I exploit two linked census panels. The first spans 1851-1861 and captures the decade prior to the diffusion of mechanized bootmaking. The second spans 1861-1881 and covers the decades after the mechanization shock. Each panel follows individuals employed in the initial census wave forward to observe whether they remain in the same occupation in the subsequent census.

I estimate the effect of mechanization on incumbent exit using a difference-in-differences design which compares changes in the exit rates of bootmakers to those of workers in other industries. I estimate the specification separately by sex. Male and female labour markets differed sharply in occupational structure, baseline exit rates, and pre-mechanization dynamics. Pooling men and women into a single triple-difference specification would therefore construct an invalid counterfactual: the implied comparison would require one sex's occupational evolution to stand in for the other's, despite their fundamentally different adjustment patterns.[9] Estimating separate models ensures that each treated group is compared only to a same-sex control group whose occupational trends provide a meaningful counterfactual.

Let $Exit_{ict}$ be an indicator equal to one if individual i in county c and census year t is observed leaving their industry between t and $t+1$. For each sex, I estimate:

$$\log\left(\frac{P(Exit_{ict}=1)}{1-P(Exit_{ict}=1)}\right) = \alpha + \theta\, Bootmaker_i + \phi\, Post_t + \beta\,(Bootmaker_i \times Post_t) + \gamma' X_{ict} + \delta_c + \varepsilon_{ict}, \tag{1}$$

[9]See Callaway and Sant'Anna (2021) and de Chaisemartin and D'Haultfoeuille (2020, 2022) on the importance of constructing subgroup-appropriate counterfactuals in settings with heterogeneous pre-trends.

where $Bootmaker_i$ indicates incumbent bootmakers, and $Post_t$ equals one for the endline census in each panel (1861 in the pre-mechanization panel, and 1881 in the post-mechanization panel). The vector X_{ict} includes demographic controls measured at baseline (age, rural/urban status, marital status), δ_c are county fixed effects.

The coefficient β captures the difference-in-differences change in the log-odds of exiting artisanal bootmaking for incumbents, relative to workers in other industries, between the baseline and endline census waves. For ease of interpretation, the results section reports $\exp(\beta)$ as odds ratios (Table 2).

Having examined the incumbent margin, I next study whether the contraction in artisanal bootmaking was absorbed through a decline in entry. To do this, I directly measure the flow of new entrants into artisanal bootmaking across counties and cohorts, and track the associated changes in the composition of the bootmaking workforce over time. These descriptive patterns then motivate the formal identification strategy used to determine why entry fell after 1861.

4.2 Why Did Entry Collapse?

The key question is whether young men were deterred from entering because the industry contracted, or because they were pulled toward expanding opportunities elsewhere. To identify the causal effect of entering a declining industry, I exploit the fact that the sons of bootmakers had always been disproportionately likely to become bootmakers themselves. This intergenerational occupational persistence remained remarkably stable, providing a group of young men whose propensity to enter bootmaking did not respond directly to local labour market conditions.

This behavioural rigidity effectively assigns the sons of bootmakers quasi-randomly across local labour markets that were differentially affected by mechanization. Some sons were born into counties in which artisanal bootmaking declined sharply, while others were born into counties where the trade remained stable or expanded. I compare outcomes for sons who became bootmakers in declining versus non-declining counties to isolate the consequences of entering a shrinking industry.

To address concerns about unobserved household and regional characteristics, I implement a within-household difference-in-differences design that compares the outcomes of treated sons —those who entered bootmaking — to those of their brothers, who did not. By differencing within families, the design removes time-invariant household-level traits which might confound the relationship between occupational choice and adult outcomes. These include parental occupation, socioeconomic status, family networks, cultural norms, genetic endowments, and the shared childhood environment. Household fixed effects also absorb time-invariant features of the local labour market in which the family lived, such as baseline employment conditions, industrial composition, or long-standing regional shocks. Together, these adjustments eliminate a broad class of potential sources of bias, allowing the remaining within-family differences to be interpreted as the causal effect of entering a declining artisanal industry.

The identifying assumption is mean independence of unobservables with respect to treatment:

$$E[U \mid T] = E[U],$$

where T indicates whether a son of a bootmaker is born into a county where the artisanal bootmaking sector subsequently declines, and U captures unobserved family- and individual-level traits. For sons of bootmakers, the stability of intergenerational persistence ensures that exposure to county-level decline is not driven by endogenous occupational sorting, making this assumption plausible.

For the sons of bootmakers who enter artisanal bootmaking, I estimate:

$$Y_{ic} = \alpha + D_{ic}'\beta + X_i'\gamma + \varepsilon_{ic}, \tag{2}$$

where Y_{ic} is an adult outcome for son i in county c; D_{ic} is a vector of indicators for whether county c is classified as having a bootmaking industry which is stable or declining (with flourishing as the omitted category); and X_i includes age and birth order. The coefficients in β measure differences in outcomes for bootmaker sons across county types. Standard errors are clustered at the county level.

For families with at least one bootmaker son and one non–bootmaker son, I estimate the within-household specification:

$$Y_{ifc} = \delta_f + \left(D_c'\beta\right) \text{BootmakerSon}_{if} + X_{if}'\gamma + \varepsilon_{if}, \tag{3}$$

where Y_{ifc} is the adult outcome of son i in family f born in county c; δ_f is a family fixed effect; BootmakerSon_{if} indicates entry into artisanal bootmaking; and D_c is a vector indicating whether the bootmaking industry in county c is stable or declining (with flourishing as the omitted variable). The vector X_{if} contains age and birth order. Standard errors are clustered at the county level.

The coefficients in β capture how the within-family difference between bootmaker and non-bootmaker sons varies across county types, identifying the causal effect of entering artisanal bootmaking when the local artisanal sector was in decline.

In this sense, the interaction coefficients in $D_c'\beta$ measure the cost of persistence: they quantify how much worse bootmaker sons fare, relative to their own brothers, when they persist in entering an artisanal trade that is locally in decline rather than stable or flourishing. If young men avoided the artisanal trade because better opportunities opened elsewhere ("pull"), then entering artisanal bootmaking should not generate systematically worse adult outcomes within the same family. In contrast, if the artisanal path itself had become a disadvantageous trajectory ("push"), then brothers who entered the trade should experience significantly worse outcomes than their non-bootmaker siblings. Household fixed effects ensure that the estimated β reflects the causal penalty associated with entering a dying artisanal industry.

5 Results

In this section, I follow the structure of the empirical strategy. I begin by examining whether mechanization displaced incumbent bootmakers (Section 6.1). I then document how the decline in artisanal employment occurred along the entry margin (Section 6.2). Finally, I turn to the causal analysis of why entry collapsed, using the behavioural rigidity of sons of bootmakers to estimate the consequences of entering a declining artisanal trade (Section 6.3).

5.1 Incumbents

I begin by testing whether mechanization displaced incumbent artisanal bootmakers. This question is central to understanding how the contraction of the trade unfolded. If mechanization had directly pushed existing workers out, we would observe a sharp rise in exit rates among incumbent bootmakers relative to workers in other industries. Conversely, if incumbents remained largely in place, displacement must have occurred along the entry margin instead. Table 2 reports estimates from logistic difference-in-differences specifications which compare changes in exit behaviour between bootmakers and workers in other occupations.

Across both panels, male bootmakers exhibit *lower* exit rates than men in other industries.[10] In 1851–1861, male bootmakers were significantly less likely to leave their occupation, reflecting the relative stability of artisanal bootmaking prior to mechanization. The interaction term for the post-mechanization period (1861-1881) shows a modest increase in the odds of exit, roughly 8 - 9% depending on the specification, but this effect is small in magnitude and far below what would be expected under substantial technological labour displacement.

[10]See Appendix H for more detail.

Table 2: Odds of Exiting

	Odds Ratios (Exit)			
	(Male)	(Male)	(Female)	(Female)
Bootmaker	0.309***	0.304***	0.897***	0.760***
	(0.011)	(0.012)	(0.032)	(0.033)
Post	1.420***	1.328***	1.526***	1.477***
	(0.003)	(0.003)	(0.007)	(0.007)
Urban 2 (Semi-Urban)		0.767***		0.755***
		(0.008)		(0.018)
Urban 3 (Semi-Rural)		0.742***		0.767***
		(0.004)		(0.009)
Urban 4 (Rural)		0.614***		0.812***
		(0.005)		(0.010)
Age		0.989***		0.996***
		(0.0002)		(0.0003)
Bootmaker X Post	1.082***	1.090***	2.270***	2.370***
	(0.016)	(0.017)	(0.056)	(0.058)
Constant	0.910***	2.098***	1.262***	2.053***
	(0.015)	(0.083)	(0.022)	(0.191)
County Controls	Yes	Yes	Yes	Yes
Marital Status Controls	Yes	Yes	Yes	Yes
Observations	1,954,948	1,784,364	550,940	494,941
Log Likelihood	-1,284,195	-1,158,147	-290,479	-260,286
Akaike Inf. Crit.	2,568,479	2,316,554	581,048	520,763

Note: Standard errors clustered at the county level. *p<0.1; **p<0.05; ***p<0.01

For women, the picture is starkly different. Female bootmakers were already in more precarious positions, and the post-mechanization period saw their odds of exit rise dramatically.[11] Their odds of leaving their occupation more than doubled relative to women in other industries. This does provide initial evidence that female bootmakers experienced substantial technological labour displacement. Because women constituted less than 20 percent of the artisanal bootmaking workforce, this displacement does not account for the large aggregate contraction of the trade, but it confirms that mechanization had a distinctly gendered impact.

One concern is that national averages may mask substantial regional heterogeneity. To assess this, I re-estimate the model separately by county and map the resulting odds ratios in Figure 13. The county-level results, reported in full in Appendix J, show that most counties display no ev-

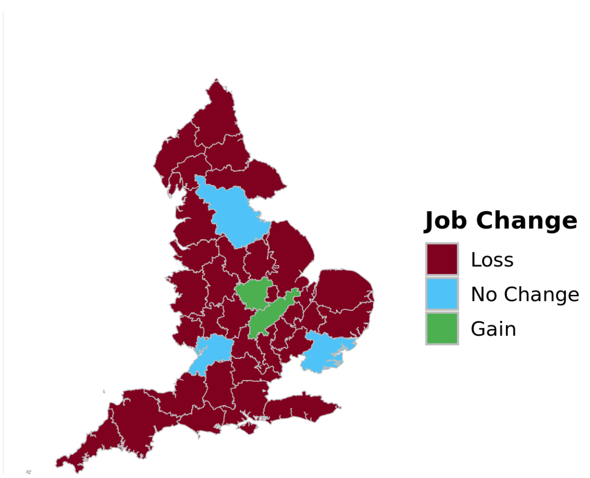
[11] See Appendix I for a discussion on women in the Census Enumerators' Books.

idence of male displacement. This reinforces the conclusion that mechanization did not significantly displace male incumbents, and that the collapse in artisanal bootmaking must therefore have occurred along the entry margin.

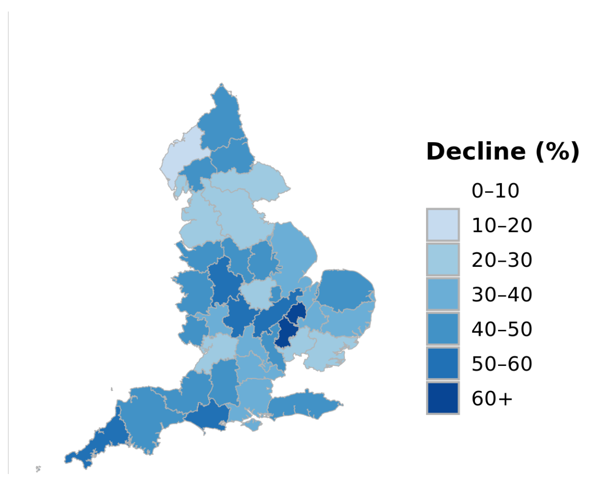
5.2 Entrants

Having found that incumbents experienced minimal technological labour displacement, the only remaining potential explanation for the contraction of the older, artisanal, bootmaking jobs is that young people increasingly chose not to enter. In this subsection, I document the collapse in new entrants and the strong geographic patterning of this response.

Figure 3 shows the change in artisanal bootmaking employment across counties. Most counties experienced substantial contraction between 1861 and 1881. A handful of counties in Northamptonshire saw growth in factory-based bootmaking, reflecting the spatial reorganisation of the industry.



(a) Overall decline/growth in the Bootmaking Industry



(b) Percentage decline in artisanal jobs

Figure 3: Bootmaking jobs and percentage decline by county.

Unsurprisingly, young men responded endogenously to these changing opportunities. Fewer entered into artisanal bootmaking occupations, which we see in the contraction of employment in these types of jobs. See the decline of entry depicted in Figure 4. As the artisanal tasks were geographically distributed, this meant that the decline of young men entering was particularly sharp in some regions.

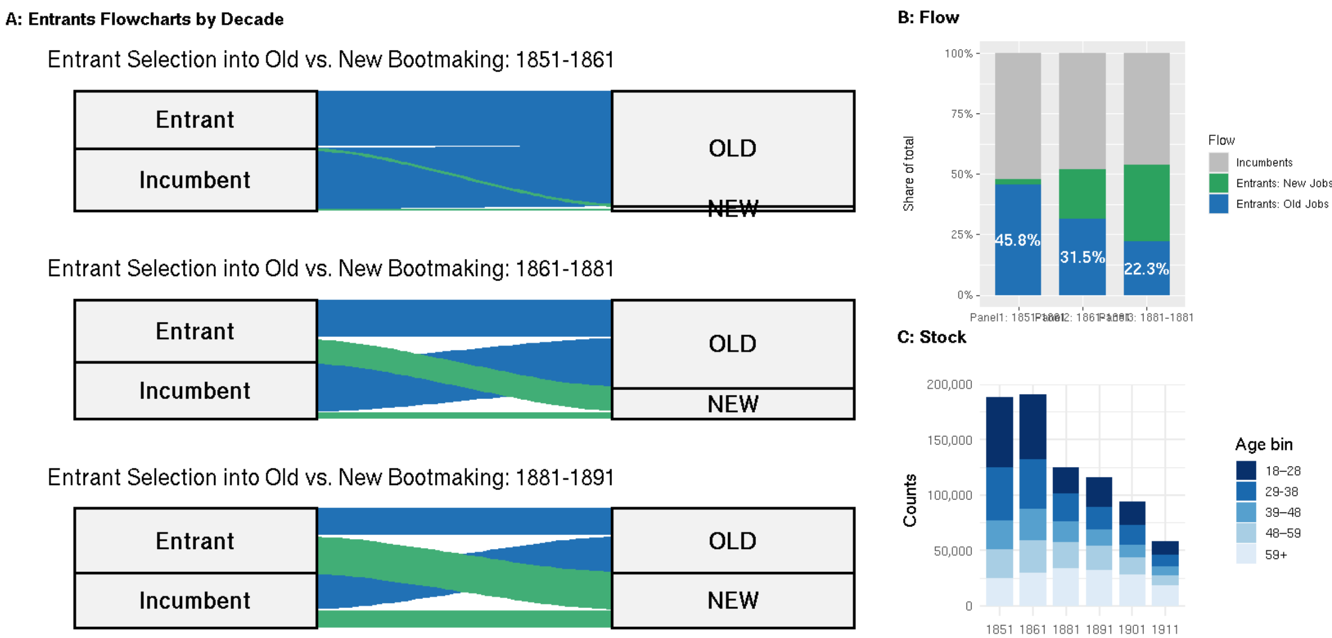


Figure 4: Entrants and bootmaking jobs by decade.

Panel A shows entrant selection into old vs. new bootmaking jobs over three periods. Note that the incumbents shown selecting into new represent the net switch of incumbents from old to new (a small share of incumbents employed in old jobs switch to new, and vice versa). The number of new jobs available in bootmaking in 1861 is very small and not labelled for readability. Panel B presents the share of incumbents, entrants into old jobs, and entrants into new jobs. Panel C shows the stock of bootmakers by age group. Observations with missing age are excluded. Flow widths are proportional to counts.

5.3 The Cost of Entering a Declining Industry

The analysis above establishes that the decline in artisanal bootmaking was driven almost entirely by a collapse in entry rather than by an increase in incumbents exiting. This collapse in entry occurred precisely as mechanization was taking hold. This raises the question - did mechanization drive young men away from the trade, or did they simply happen to voluntarily be shifting toward better opportunities elsewhere?

To disentangle, I examine whether persisting in artisanal bootmaking after the shock would have carried a cost. If the trade offered increasingly poor prospects, this would indicate that the decline in entry was driven by the mechanization shock itself rather than by expanding opportunities in other sectors. Conversely, if persistence had carried no costs, then the decline in entry would be more consistent with voluntary reallocation.

Identifying this "cost of persistence" is challenging, because we cannot directly observe the outcomes of those young men who would have become bootmakers had artisanal jobs still been available. However, the sons of bootmakers provide a unique window into this counterfactual. Historically, they were disproportionately likely to enter the trade, and this behaviour remained remarkably stable over time. Among sons under age nineteen living with their families in the base year, roughly 25–30 percent became bootmakers themselves. This rate changes little across the 1851, 1861, and 1881 cohorts and remains nearly constant across county types (Table 9). Even in counties in which artisanal bootmaking declined sharply, sons of bootmakers continued to enter the trade at similar rates as they had previously.

This behavioural rigidity is economically significant. In most occupations, young workers adjust their choices in response to changing labour demand, a feature emphasised in the Roy (1951) model and the literature on endogenous occupational choice (Heckman 1979). Here, however, persistence blocks reallocation. The dynamics which normally complicate causal inference becomes the source of identification: because sons of bootmakers persisted, and did not fully alter their entry behaviour in response to mechanisation, exposure to a declining or flourishing artisanal labour market is effectively exogenous for this group.

Before turning to the regression analysis, I begin with descriptive evidence on the outcomes of sons of bootmakers across different regional labour market conditions. See Table 3, below.

Table 3: Outcomes of Sons of Bootmakers by County Type, 1861–1891

	Sons who became bootmakers			Sons who did not become bootmakers			
County type	Married	Head	Migrated	Married	Head	Migrated	HISCAM
Decline	78.9	85.0	23.5	84.7	86.5	34.2	47.9
Growth	87.3	88.3	13.9	84.3	86.4	33.9	49.2
Steady	82.4	86.0	15.6	84.3	86.0	24.6	48.5

Notes: Table reports outcomes for sons of bootmakers (SOBs), by county bootmaking trajectory between 1861 and 1891. Left panel: SOBs who became bootmakers. Right panel: SOBs who did not. Outcomes include marriage, household headship, migration.

The descriptive patterns in Table 3 already reveal substantial divergence across county types. Among sons of bootmakers who became bootmakers themselves, those born in counties in which artisanal bootmaking declined fare noticeably worse on every dimension. Their marriage rates are lower, their likelihood of becoming household heads is lower, and their migration rates are substantially higher, consistent with being pushed out of deteriorating local labour markets. By contrast, sons who entered bootmaking in flourishing counties exhibit the strongest outcomes, with higher marriage and headship rates, and markedly lower migration.

Equally important is the comparison with their brothers. Only about 25 percent of sons of bootmakers became bootmakers themselves; the remaining 75 percent entered other occupations. If the technological shock operated through broad regional hardship or family background effects, we would expect these non-bootmaker brothers to show similar divergences across county types. Instead, their outcomes are remarkably similar. For the sons of bootmakers who did not become bootmakers, marriage rates, headship rates, and even migration probabilities are nearly identical across counties in which the bootmaking industry is declining, stable, or flourishing. In other words, the technological shock does not appear to affect sons who did not follow their fathers into artisanal bootmaking.

This contrast isolates the mechanism. The penalties associated with declining counties appear only for sons who persist in entering the bootmaking trade. Their brothers, who share the same family background and are exposed to the same local economic conditions, show no comparable divergence across county types. They are not directly impacted by the technological shock to the industry. This pattern strongly suggests that it is persistence in a deteriorating occupation, rather than general family disadvantage or broader regional hardship, that drives the poorer outcomes for the sons who become bootmakers in counties in which the industry is in decline.

The regression results in Table 4 confirm the patterns visible in the descriptive evidence. Sons of bootmakers who entered the trade in counties where artisanal bootmaking declined experienced significantly worse adult outcomes on every margin. Relative to sons entering the trade in counties in which the industry was flourishing, those in counties in decline are 5–8 percentage points less likely to marry (cols. 1–2) and 2–3 percentage points less likely to become household heads (cols. 3–4). The migration results are even starker: bootmakers in declining counties are 8–10 percentage points more likely to leave their home county than those in flourishing areas (cols. 5–6). These effects are substantial given the baseline migration rate of roughly 19–25 percent.

Table 4: Sons of bootmakers who become bootmakers

	Dependent variable:					
	Married at tp2		Head of household at tp2		Migrated by tp2	
	(1)	(2)	(3)	(4)	(5)	(6)
Stable county	-0.062^{***}	-0.047^{***}	-0.024	-0.027^{*}	-0.020	-0.009
	(0.022)	(0.018)	(0.015)	(0.016)	(0.042)	(0.042)
Decline county	-0.076^{***}	-0.054^{***}	-0.025^{***}	-0.029^{***}	0.081^{***}	0.097^{***}
	(0.014)	(0.012)	(0.009)	(0.009)	(0.031)	(0.032)
Age at tp2		-0.008^{***}		0.001^{**}		-0.005^{***}
		(0.001)		(0.0004)		(0.001)
Birth order		-0.017^{***}		-0.007		-0.001
		(0.005)		(0.005)		(0.006)
Constant	0.863^{***}	0.989^{***}	0.894^{***}	0.894^{***}	0.188^{***}	0.254^{***}
	(0.010)	(0.015)	(0.004)	(0.012)	(0.027)	(0.036)
Observations	7,906	7,906	7,906	7,906	7,906	7,906
R^2	0.007	0.034	0.001	0.002	0.012	0.024
Adjusted R^2	0.007	0.033	0.001	0.002	0.012	0.023

Note: Standard errors in parentheses. $*$ p<0.1, $**$ p<0.05, $***$ p<0.01. Sample restricted to sons of bootmakers under 18 at tp1 living with their fathers

To isolate these effects from unobserved family background and to strengthen the causal interpretation, I next turn to the within-household design outlined in the empirical strategy. This approach restricts the sample to families with at least one son who became a bootmaker and at least one son who did not, thereby allowing me to difference outcomes within the same household. Because brothers share the same parents, childhood environment, and local conditions at birth, comparing their outcomes removes all time-invariant family-level heterogeneity that could confound the relationship between occupational choice and adult outcomes.

The identifying variation now comes from how the within-family gap between the bootmaker son and his non-bootmaker brother differs across county types. If it is persistence in the artisanal trade, rather than family disadvantage or general regional hardship, which drives the poorer outcomes observed in declining counties, then these differences should be visible within families as well. I estimate the family fixed-effects specification in Equation (3) and present the results in Table 5

Table 5: Within Household Differencing

	Dependent variable:					
	Married at tp2		Head of household at tp2		Migrated by tp2	
	(1)	(2)	(3)	(4)	(5)	(6)
Bootmaker son	0.023	0.023	0.047	0.043	-0.128^{***}	-0.124^{***}
	(0.042)	(0.040)	(0.035)	(0.032)	(0.024)	(0.025)
Stable county	0.020	0.039^{*}	0.014	0.023	-0.029^{**}	0.019
	(0.015)	(0.021)	(0.012)	(0.020)	(0.012)	(0.028)
Decline county	0.029^{*}	0.115	0.008	0.060	-0.328^{***}	-0.119
	(0.017)	(0.086)	(0.014)	(0.091)	(0.016)	(0.110)
Age at tp2		-0.004		-0.003		-0.009^{*}
		(0.004)		(0.004)		(0.005)
Birth order		-0.018		-0.030^{**}		-0.026
		(0.014)		(0.014)		(0.024)
Bootmaker $\times$ Stable	-0.061	-0.062	-0.041	-0.046	0.087^{**}	0.091^{**}
	(0.045)	(0.046)	(0.037)	(0.038)	(0.035)	(0.038)
Bootmaker $\times$ Decline	-0.067	-0.067	-0.032	-0.040	0.032	0.038
	(0.047)	(0.049)	(0.039)	(0.040)	(0.037)	(0.039)
Constant	0.992^{***}	1.082^{***}	0.984^{***}	1.090^{***}	0.376^{***}	0.548^{***}
	(0.014)	(0.081)	(0.012)	(0.084)	(0.008)	(0.117)
Observations	4,338	4,338	4,338	4,338	4,338	4,338
R^2	0.466	0.467	0.429	0.432	0.571	0.573
Adjusted R^2	0.090	0.090	0.027	0.031	0.268	0.271

Note: Standard errors in parentheses. Sample restricted to sons of bootmakers under 18 at tp1 living with their fathers Columns (2), (4), and (6) additionally control for age at tp2 and birth order. $*$ p<0.1, $**$ p<0.05, $***$ p<0.01.

In sum, then, the bootmaking industry went into decline in the majority of the English counties following mechanization. In these places, incumbents were protected from the storm of creative destruction. However, young men increasingly declined to enter into the dwindling industry. The young men who did continue to enter, heedless of the changed labour market conditions, experienced a reduced quality of living. I turn to a discussion of the relevance of these findings.

5.4 Mechanism

How did incumbents remain in place while young men left the industry? I show evidence that the demand for artisanal boots persisted in some places.

This section considers potential mechanisms for the different experiences of labour displacement as the English bootmaking industry mechanized. I explore two questions: firstly, why was there such a divergent experience in terms of labour displacement for male and female incumbents? Secondly, were there trends in the geographical variation in labour displacement experienced by incumbent men?

Male and female incumbent bootmakers experienced sharply different magnitudes of labour displacement as the English bootmaking industry mechanized. The divergence can potentially be explained by differential changes in demand for labour. The majority of women working in the English bootmaking industry - 95% - worked as binders. They sewed together the uppers of shoes and boots by hand. The adoption of the sewing machine comprehensively replaced this work, and demand for this kind of labour disappeared almost entirely. Male bootmakers, on the other hand, faced a different labour market. They were skilled craftsmen, producing bespoke, high quality footwear. As the bootmaking industry mechanised, production of footwear shifted to lower quality, less expensive "ready-to-wear" goods. Demand for bespoke shoes did not, however, immediately vanish.

I show below that artisanal bootmakers, producing bespoke goods, were over-represented in wealthy parishes in England. Demand for new boots and shoes largely came from wealthier individuals, with working-class people often buying second hand shoes. I hypothesize that demand for bespoke shoes persisted in these wealthier areas, sustaining demand for the older forms of skilled labour specialized in bespoke boots and shoes. To analyze this, I run a linear regression where the dependent variable is bootmakers per capita. I run this separately for bespoke bootmakers and, in 1881, for bootmakers working in the new "ready wear" tasks. Independent variables include a measure of wealth, population size, and a measure of urbanisation, at the parish level. Population size is included because more dense areas may be more economically diverse, which could affect the demand for artisanal products. The regression specification is below.

$$\text{BootmakerDensity}_i = \beta_0 + \beta_1(\text{Wealth}_i) + \beta_2(\text{Population}_i) + \beta_3(\text{Urban}_i) + \epsilon_i \tag{4}$$

The results, in Table 6 below, show that there is a fairly strong positive correlation between the location of bespoke bootmakers and the wealth of a parish in 1851 and 1861, prior to mechanization. In this period all bootmakers were producing bespoke footwear. In 1881, however, there is a sharp change. The strong correlation persists for bootmakers working in the old types of bootmaking tasks, but disappears completely for bootmakers working on the "new" bootmaking jobs.[12]

[12]Please see the wealth maps in the Appendix G for a visualization of the distribution of wealth by district in England at this time. This "wealth map" is simply the distribution of people in the top 10% of upper tail human capital, as measured by HISCAM scores. The second wealth map is based on income data.

Table 6: Bespoke Bootmaker Density in Parishes with Top Human Capital

	Dependent variable: Bootmakers per 10,000			
	(Bespoke 1851)	(Bespoke 1861)	(Bespoke 1881)	(Ready Wear 1881)
Share_Top_HC	4.047***	4.211***	2.034***	-0.698**
	(0.426)	(0.497)	(0.281)	(0.284)
Population	0.009***	0.006***	0.001**	0.0002
	(0.001)	(0.001)	(0.001)	(0.001)
Urban 2	-100.529***	-107.435***	-33.405***	-67.654***
	(12.244)	(12.972)	(6.613)	(6.677)
Urban 3	-61.877***	-81.191***	-8.717	-67.489***
	(9.627)	(10.644)	(5.845)	(5.901)
Urban 4	-77.578***	-94.777***	-7.745	-85.439***
	(9.683)	(10.723)	(5.770)	(5.825)
Constant	236.287***	242.216***	100.703***	92.467***
	(10.545)	(11.688)	(6.216)	(6.275)
Observations	14,317	14,488	13,933	13,933
R^2	0.037	0.031	0.011	0.023
Adjusted R^2	0.037	0.031	0.010	0.023
Residual Std. Error (df)	238.542 (14311)	261.073 (14482)	149.742 (13927)	151.171 (13927)
F Statistic (df)	110.547*** (5; 14311)	92.616*** (5; 14482)	29.773*** (5; 13927)	66.336*** (5; 13927)
Note:	*p<0.1; **p<0.05; ***p<0.01			

There is some research which discusses the demand side of markets during the British Industrial Revolutions. Kelly and Ó Gráda (2016) suggest that, without a sufficiently prosperous middle class, the innovation and labour specialization they find in the British watchmaking industry could not have existed. Heller (2008) finds that salaries for male clerks in London increased over the latter half of the 19th century. Boot (1999) makes use of data on the earnings of clerks employed by the East India Company in the previous century to generate an index of middle-class living costs. He, too, is finding a steady increase in wages, between 1780-1840. Middle and upper class demand for bespoke boots and shoes may have persisted for some time. In fact, some remnant of it persists even to the modern day: there are still companies producing handmade bespoke shoes in Northamptonshire.

5.5 Conclusion

Recent scholarship has focused on labour displacement driven by the adoption of new technologies. A very large body of work has assessed how exposed workers are to labour displacement (Frey, 2019). Another, albeit smaller, body of work has begun to explore the consequences of occupational decline for workers and their families (Edin et al., 2019; Feigenbaum and Gross, 2020; Cockriel, 2023)). In policy briefings, from the OECD to the MIT report on the Future of Work, the impact of labour displacing technological change is conceptualized as displacing existing workers. It is one reason why much of the policy focus on mitigating the impacts of the adoption of labour displacing technology is on retraining.

This paper provides a case study in which the incidence of the shock was not primarily experienced by existing workers. It had minimal impact on incumbent male bootmakers, who represented 80% of the bootmaking workforce, although it may have impacted women considerably more. The primary impact of the shock impacted the matrix of opportunities available to young people. It did so on a geographical basis, making bootmaking a less viable option for young people across most of England. If the adoption of this new technology generated inequalities, it did so primarily by way of changing the set of opportunities available to young people.

This provides a tighter tie to earlier understandings of the impact of technological change on the labour market. In the approach proposed by Skills Biased Technological Change, and the race between education and technology, the model is one in which demand for new skills at times outstripped supply, and led to skill premiums. The conclusions of this paper do not revolve around potential wages in new occupations, but around access to employment. It is the reverse of labour displacement heterogeneously distributed by geography: it is employment opportunity which is heterogeneously distributed.

I do not argue that all labour displacing technology will be of this type, and impact primarily on young people. However, some events may be structured in this way, and it would be valuable to develop a better understanding of which groups are primarily impacted, and why. Creative destruction has been ongoing for more than 200 years. In this period hundreds of thousands of jobs have been made obsolete, and have disappeared. 60% of the jobs which existed in 1940 no longer exist in America in 2020 (Autor et al., 2022). At the dawn of the age of technological adoption there was considerable concern that the new machines would steal jobs. This concern quietened considerably over time. Did we manage to destroy all those jobs without causing substantial damage? If so, how? The answer given at the moment is that new jobs were created at least as fast as old jobs were lost, and there is some assumption that incumbents retrained and moved into the new jobs. In this paper I show evidence from a case study in which incumbents neither moved into more jobs, nor faced labour displacement, because the margin of adjustment was in the set of opportunities available to young people.

One key component of this must have been the speed at which the industry shifted from old production processes to new ones. It is not unusual for the adoption of new technology to take considerable time. The steam engine took many years to replace the watermills in England. Steamships took decades to replace sail. Under these conditions, it may be more possible to grandfather out older workers. However, as the speed at which new technologies replace the old increases, this may become less feasible. There is some evidence, from the recent adoption of AI large language models, that incumbents in the industry have become entrenched, while it has become considerably more difficult for young people to find employment in the tech industry.

As the sizeable bootmaking industry of Victorian England mechanized, and transitioned into new structures and places, it did not over-run its incumbent workers. Male bootmakers experienced very little labour displacement, with perhaps an increase in exit rates of around 5%. They continued to work in the traditional bespoke employment for which they had trained. Incumbent women did experience technological labour displacement. However, given that approximately 80% of the bootmakers in 1861 were male, the majority of incumbent bootmakers did not experience displacement.

The disappearance of 154,000 jobs in the "old", artisanal tasks of bespoke bootmaking were primarily the result of young men not entering the industry. I show that, had they done so, they would have borne costs. However, they did not. It is less clear whether the disappearance of employment opportunities in bootmaking had a negative impact on young men. This would have depended on opportunities in local labour markets, or the ability of these young men to migrate.

Research and policy frameworks typically view labour displacement as an issue primarily impacting existing workers. My study, however, identifies young people as a significant locus of impact, as the job opportunities they once had disappeared. Not all technologies would have been of this type, but it would be valuable to draw a distinction between the types of labour saving technologies which are more likely to impact existing workers, and those which are more likely to impact access to opportunity for future generations.

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6 Appendices

6.1 Appendix A: Article from the Northampton Mercury

Article from the *Northampton Mercury* regarding the introduction of the bootmaking sewing machine in Northamptonshire.

> *Northampton Mercury*, 8 April 1865
>
> Dear Sir,
>
> Having read in your journal of Saturday last an article extracted from the *Builder* on the above subject, I wish to make one or two corrections in it. In the first place I beg to say I was the first introducer of the sewing machine into this town in 1857. At that time I was foreman to the London and Norwich Shoe Company. Being in the United States in 1851 and '52, I saw the machine in the factory of Messrs. J. M. Singer and Co. It struck me with a little alteration as being peculiarly adapted for boot and shoe closing. On returning to England and settling in Northampton, the idea still haunted me, and in 1857 I sent for a machine (the invoice of which I still have by me) being determined to test it. I did so, and the result convinced me that my first impression

was right. On its becoming known a deputation waited on me, and requested me to get rid of the machine, which I refused to do. From that time commenced a strike of from 15 to 18 months' duration, the whole of which time I was followed to and from my home by several hundreds of people daily, who swore they would drive me and my machine out of town together. The fallacy of which threat is proved by the fact of there being upwards of 1500 in the town at the present time. We all know you to be a lover of fair play, and that you endeavour to give honour where honour is due, therefore your insertion of the above will oblige,

W. Young Edward
Northampton Mercury, 8 April 1865

6.2 Appendix B: Construction of the "Bootmakers" Group

The group of "English Bootmakers" could be defined in various ways. I use the complete census data for England and Wales, for all six census returns between 1851-1911 (excluding 1871). The data is then filtered down to the four bootmaking industries: categorized as 663, 664, 665, and 666 with the ICeM project's time-invariant variable for occupation. All individual level observations are aggregated together into one dataset. This contains 1,391,852 observations of bootmakers in England and Wales between 1851-1911. I filter to bootmakers born in England, which leaves 1,330,646 observations.

Finally, I remove all individual observation in which "retired", "formerly", or "unemployed" appears in the text description of the occupation. There may be a concern as to whether the four main occupational codes for bootmakers have captured the large majority of bootmakers. It may be the case that many bootmakers are, erroneously, recorded under other occupational codes. I therefore run a search for bootmakers in other "industry" codes. Given that this returns only a few thousand bootmakers I do not include them.

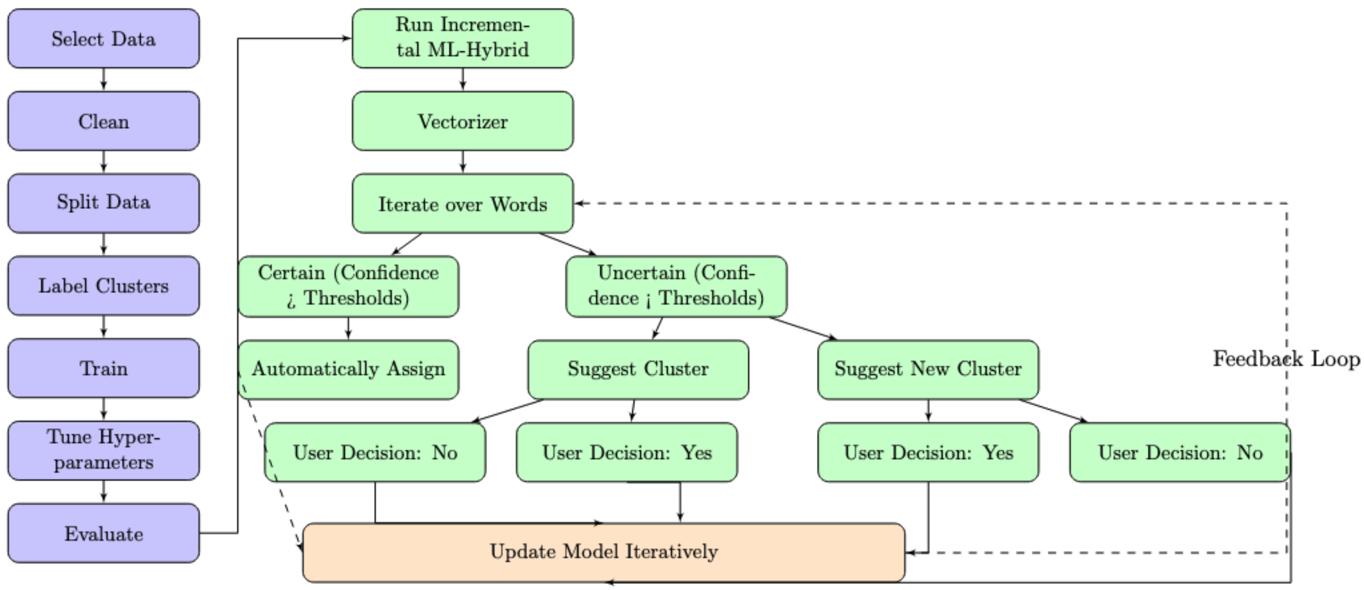
It is worth noting that the bootmaking group is unusual in being so well collected by the industry variables in ICeM. Each census taking between 1851-1911 had its own set of "Industries".

When the ICeM project digitized the British census data, they constructed a "time invariant" set of categories for occupation. This cuts across the different decennial categories in the census data, and the result is that people of the same occupation sometimes are collected into different "time invariant" bins. As an exceptionally large industry, bootmakers had a category (or several), in each of the decennial census reports. This has meant that the time invariant category in ICeM does capture them quite well.

6.3 Appendix C: Topic Modelling, "Tasks"

My approach to topic modelling is twofold. I make use of the deterministic approach described in the paper. I also use incremental machine learning, please see the model I employ in Figure 6, below.

I take an incremental machine learning approach to topic modeling for two main reasons. Firstly, while the straightforward deterministic model I employ for bootmakers is effective, it does not scale efficiently. This limitation becomes apparent as I extend my analysis to Task data across all industries. The machine learning approach scales. To ensure accuracy, I use the results from the manual deterministic approach as a ground truth for validation. Secondly, I 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.



6.4 Appendix D: Hierarchy of Keywords

Tasks are assigned to the textual descriptions in sequence. Any textual description which contains more than one task keyword is assigned to the task category ranked highest in the hierarchy specified. For example, if an individual's occupation is recorded in the text as "sewing machinist in factory, uppers", they are categorized as machinists rather than factory workers. The hierarchy is set to maximize the extraction of the most granular information about what type of work individuals were doing. Please see Table 4 below.

Table 7: Hierarchy of Keywords

1. machinist	10. finisher	19. eyeletter
2. factory	11. laster	20. trimmer
3. employer	12. fitter	21. packer
4. manufacturer	13. closer	22. dealer
5. binder	14. rivetter	23. cordwainer
6. repairer	15. operator	24. clogger
7. presser	16. foreman	25. slipper
8. manager	17. cutter	26. maker
9. clicker	18. sewer	

There are 9665 descriptions of task which contain more than one task key keyword. This represents 51 155 of the total observations (some of these descriptions are observed multiple times), or 3.8% (51 155/1 330 644). There are three dyads which each have more than 6000 observations: maker-dealer, clogger-maker, and maker-repairer. None of the dyads following have more than 2000 observations. The distribution of these is as shown below in Figure 7.

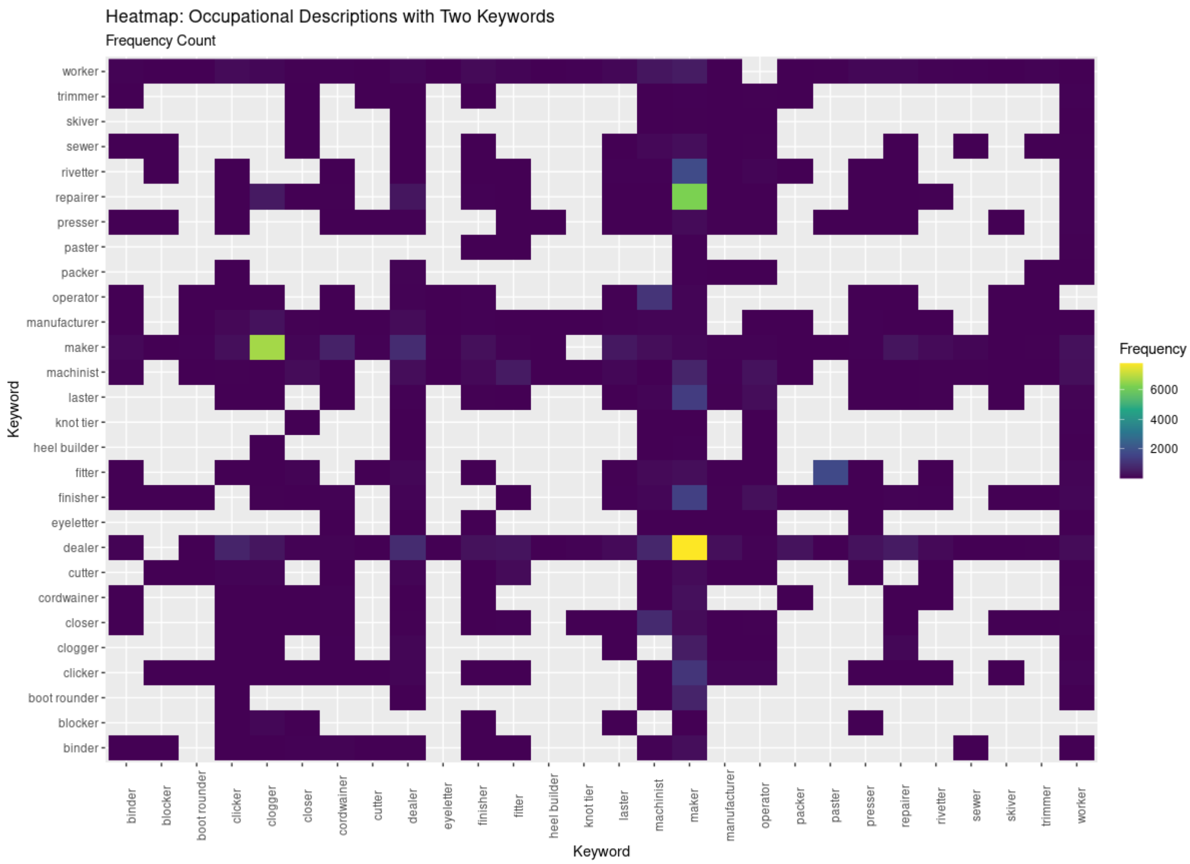


Figure 5: Heatmap of Dyads

As there are only a relatively few number of entries which could potentially be coded to two or more types of task in the bootmaking industry the choice of the hierarchy does not make a substantial impact to the results. See Table 5, below for an example of the difference it makes to place machinist first versus last in the hierarchy.

Table 8: Bootmakers identified as "Machinists" by hierarchy order

	1851	1861	1881	1891	1901	1911
Machinist: if first in hierarchy	0	272	11167	16471	24345	19428
Machinist: if last in hierarchy	0	183	10325	15266	21524	16115
Difference	0	89	842	1205	2821	3313
Difference in percent	0	32%	7.50%	7.30%	11.60%	17.10%

Note: Difference in number of Bootmakers identified as "Machinists" by changes to the order of the hierarchy which manages descriptions of tasks in which there is more than one keyword. Source: Task data derived by author from ICeM data.

There are four types of keywords which emerge in the “tasks” category. The first group of keywords is those which provide the greatest precision in describing occupation. For bootmakers, this includes nomenclature such as: clicker, fitter, repairer, dealer. This group most closely aligns with the standard meaning of “task”. The second group refers to occupational titles which are a bit more generic: for example ”foreman”, ”factory worker”, ”employer”. These are terms which emerge as technological change alters the structure of work, and production becomes increasingly based in factories. The third group refers to the materials being used: for example, a slipper maker vs a bootmaker. Finally, there is a set of “catch-all” terms, including “makers, workers”. The hierarchy of keywords places the specific keywords highest, then the supervisory type roles, then those with information regarding material, and then the most general terms. This ensures that the greatest amount of information is extracted from the strings describing occupation.

6.5 Appendix E: Nomenclature

The findings in this paper hinge on the claim that the changing descriptions of occupation in the census records reflect real changes within the occupational structure, rather than simply changing nomenclature. There are four reasons to believe this is the case.

Firstly, there is overwhelming evidence that the structural change within the bootmaking industry, by analysing the text in descriptions of occupations in the census records, did take place. Narrative histories of the mechanization of the bootmaking industry, in Britain and in the United States, confirm it. It is also visible in the changing "tasks" described in another data source, the dictionaries given to clerks assigning individuals to industries. Please see Appendix J. These dictionaries were constructed from underlying trade dictionaries, and a direct survey of manufacturers in 1881.

Secondly, the new jobs emerge primarily in Northamptonshire and Leicestershire. See the map in Figure 17 below. It would be challenging to explain this exceptionally non-random emergence of the new "nomenclature". Additionally, as discussed at length in the section on the geography of employment, the new jobs disproportionately emerge in places where there are large bootmaking companies, and indications of factory work. See Figure 16.

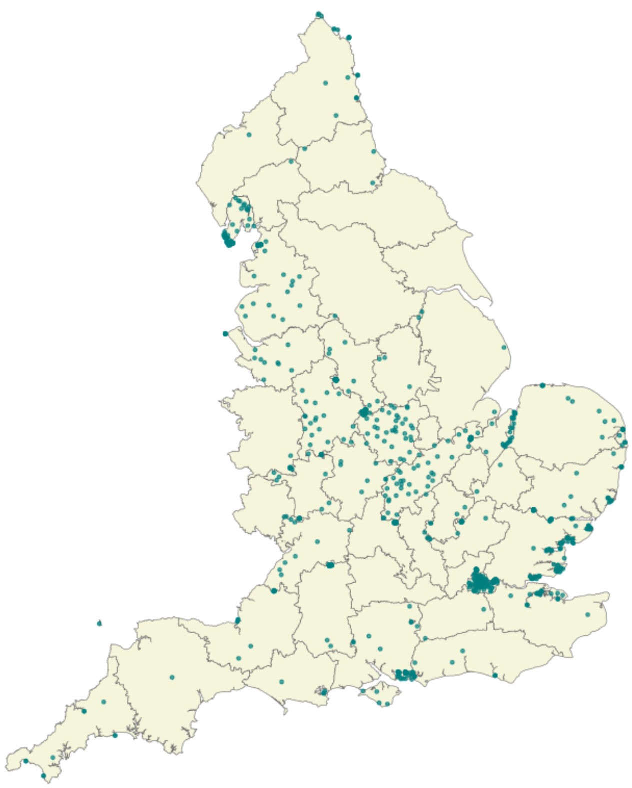


Figure 6: Large Bootmaking Companies

Note: Distribution of Large Bootmaking Companies in England in 1881. Large is defined as greater than 10 individuals employed.

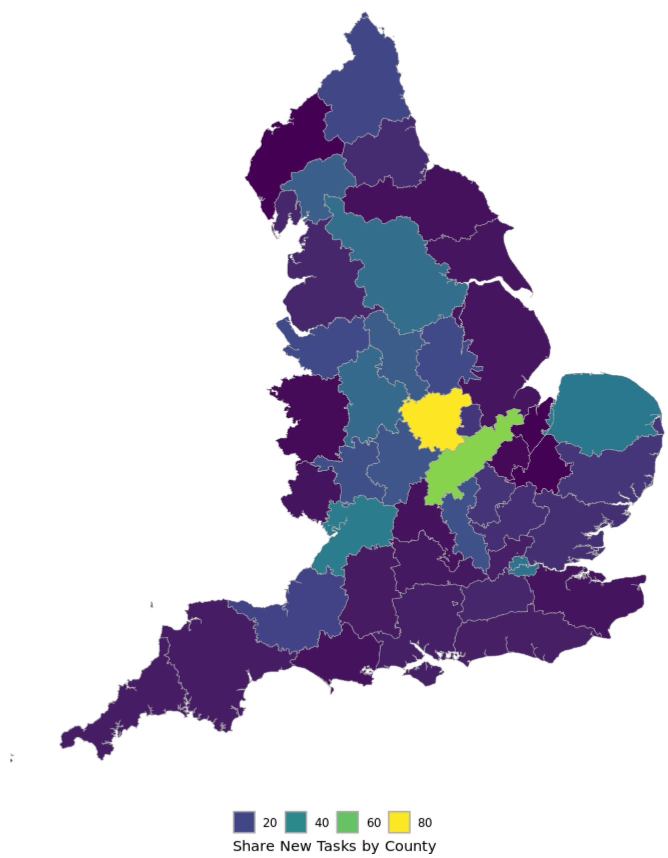


Figure 7: New Bootmaking Tasks

Note: Data derived by author from ICeM Project Data. Showing the share of new bootmaking tasks by county in 1881.

Thirdly, there is non-random distribution of tasks by age. From 1881 we start seeing a few tasks which are occupied almost exclusively by teenagers. These are “knot-tiers”, “eyeletters”, and "heel-builders". See the table and graphs below. This consistency makes it unlikely that individuals were described as working in these tasks if they were not. However, it provides no evidence that people who were working in these tasks were not classified as something else. Prior to 1881 young people documented as working in the industry are often listed as apprentices/assistants to bootmakers, cordwainers, or cloggers.

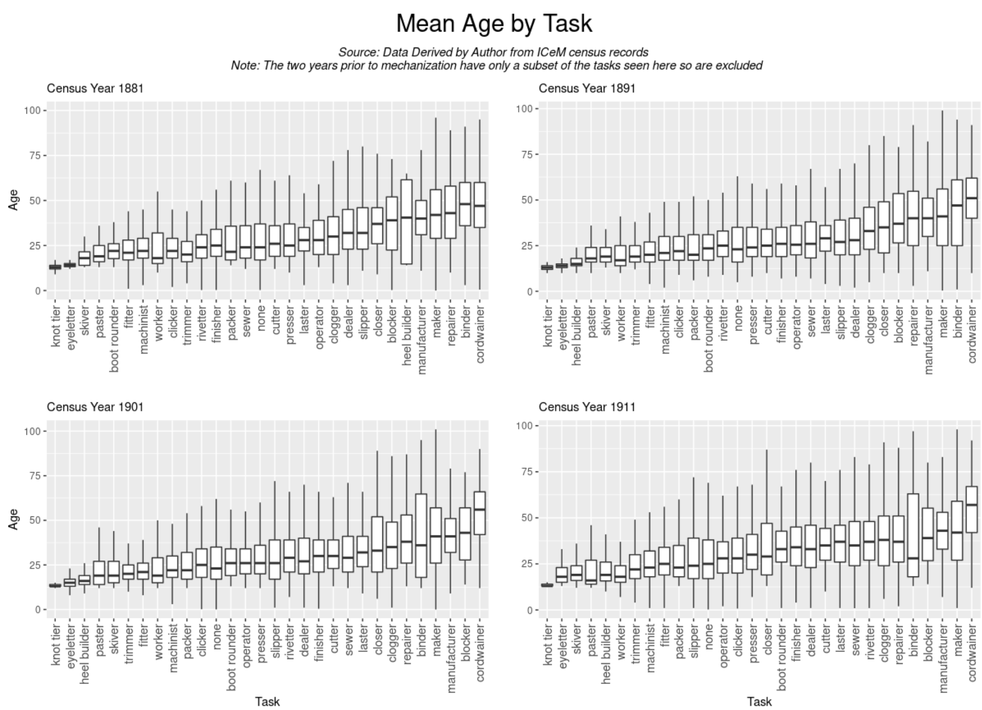


Figure 8: Task by Age, English Bootmakers

Fourthly, the consistency of the data in responding to known technological shocks. The bootmaking sewing machine first emerged in 1858, and was adopted quickly over the next two decades. It replaced the task of sewing the uppers of the boots by hand. There are no observations of bootmaking sewing machinists in the census records of 1851. There are only a handful in 1881. However, by 1881, there are thousands of sewing machinists, and binders - the women who sewed the boots and shoes by hand - have almost entirely disappeared. The disappearance of the binders is remarkably consistent: across all of England, in every district, nearly 90% of the binders disappear. There were 43 000 census enumerators, who did not co-ordinate, so this consistency in the data is remarkable. Figure 18, below, shows the distribution of the share of binders lost across districts. Binders are shown in the third row. The black lines show the 5%

tails of the distribution. The observations are for each district in England, so this is showing that the vast majority of districts in England lost 70-100% of their binders.

Thesis/Paper1/Graphs_Appendix/District_Greater15.pr

Figure 9: The Decline of the Binders

Finally, I find that individuals who remain bootmakers over time quite consistently describe themselves as having the same task they did in the previous period. That is, people who describe themselves as cordwainers in the first period describe themselves as cordwainers in the second period. This is very nearly 70% in multiple matches.

6.6 Appendix F: Pace of Change

The technological shock of mechanization did not unfold uniformly across the six decades between 1851-1911. The sewing machine was not introduced until 1858. In the first decade, between 1851-1861, prior to mechanization, there is no clear sign of job loss and job creation. However, between 1861-1881, the old jobs are in decline in nearly every single English county.

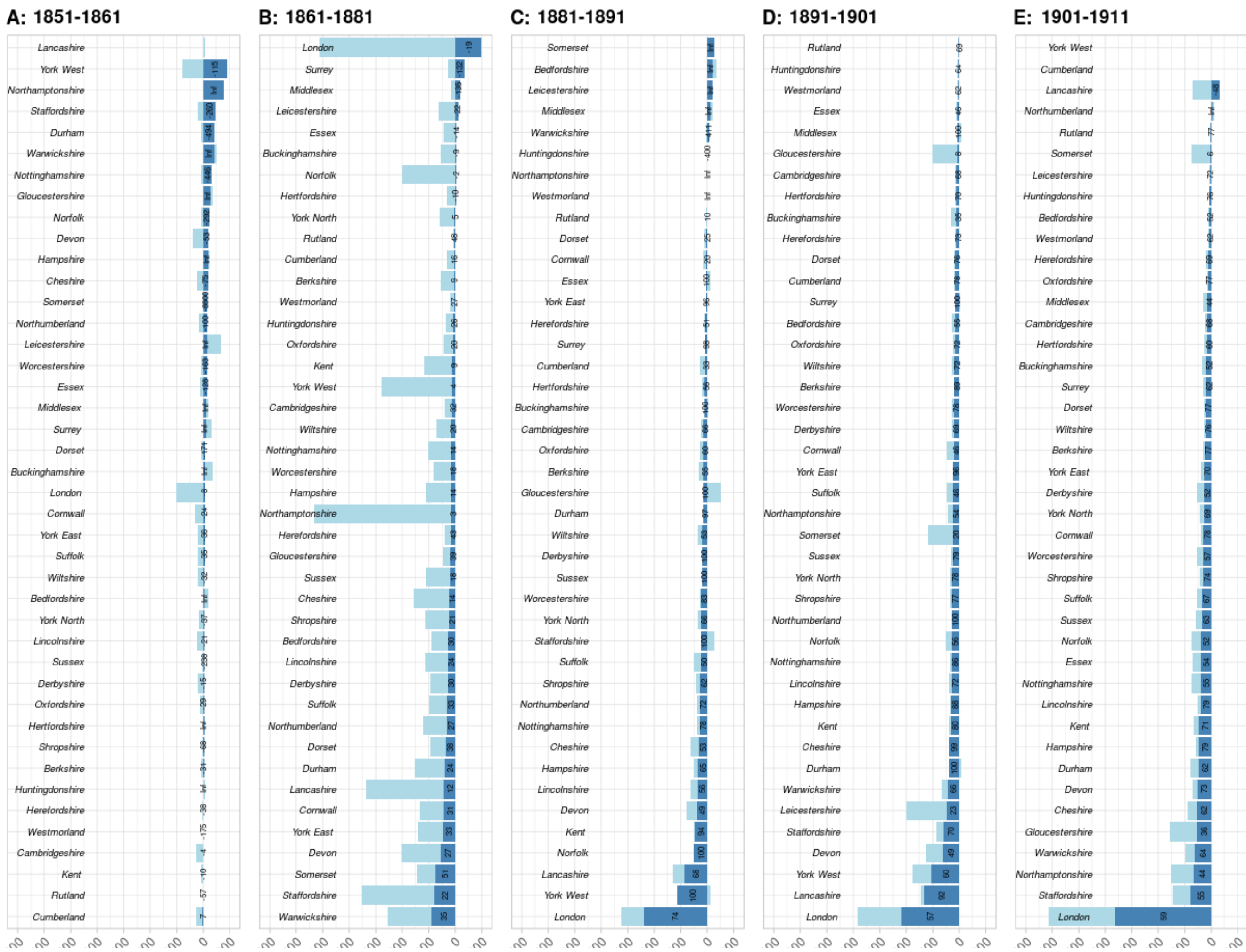


Figure 10: Change in Number of Bootmakers Employed: 1851-1861

6.7 Appendix G: Incumbent Exit

Figure 12 presents a Sankey diagram that traces the transitions of incumbent bootmakers between 1861 and 1891. It shows, separately for men and women, the share who remained in the old artisanal tasks, the share who moved into the new factory-based tasks, and the share who exited the bootmaking industry altogether. The widths of the flows are proportional to the number of individuals making each transition, allowing the relative importance of each adjustment margin to be visualized at a glance. For both men and women, a vanishingly small share of incumbent bootmakers transitioned into the new bootmaking jobs.

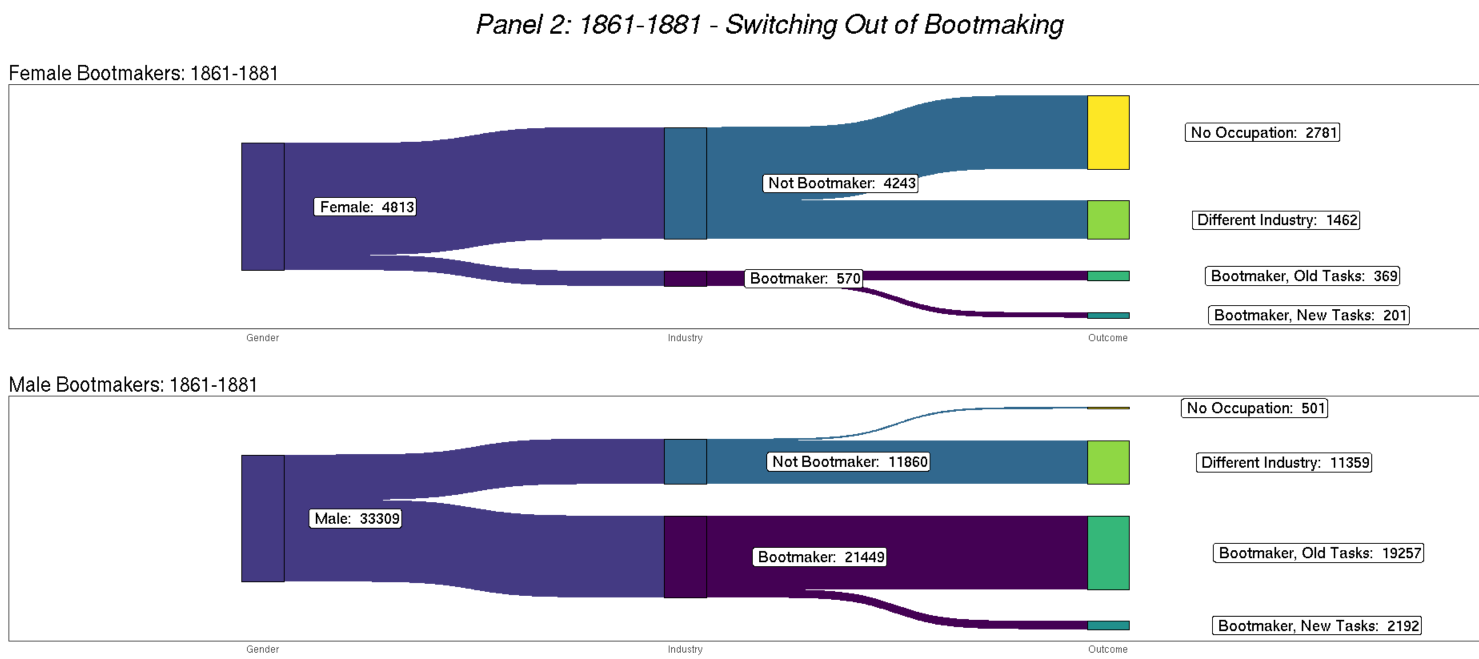


Figure 11: Incumbents

6.8 Appendix H: Distribution of Exit Rates

This section shows the distribution of exit rates, by gender, before and after the shock

Once I have calculated exit rates for all industries in both panel datasets, I construct a weighted kernel density function, which is simply the probability distribution of exit rates for all industries in each time period, by gender. [13]

$$\text{Weighted kernel density:} \quad \hat{f}(x) = \frac{1}{n} \sum_{i=1}^{n} w_i \cdot K\left(\frac{x - x_i}{h}\right)$$

Refer to Figure 3, below, for the depiction of the range of exit rates, for men and women, in both periods. These show the distribution of exit rates as calculated by the kernel density functions

[13]Weighting is to account for industries being of dramatically different size: in the calculation of weighted average rates of exit across all industries, the handful of dentists will receive less weight than the thousands of farmers.

above. The weighted average rate of exit (from all industries) is shown by the dotted black line in the figures. The exit rates for bootmakers are highlighted in red, along with a measure of their deviation from the weighted average exit rate. Considering exit rates primarily in relation to the mean and variance standardizes and controls for the fact that Panel 1 spans a ten-year period, whereas Panel 2 covers a twenty-year period.

The top panel of Figure 3 shows that male bootmakers have considerably lower rates of exit than men in most other industries. They are well below the national mean in both periods. [14]. As an industry, it is the forth most stable available to men. Bootmaking was a highly skilled trade, often requiring a full 7 year apprenticeship to master, and involved considerable investment in human capital. Notably, the exit rate for male bootmakers relative to the mean exit rate remains almost identical between the two periods, at 27 percentage points below the mean. While there is an absolute increase in exit rate, this is expected due to the longer duration of the second period.

[14]The mean is calculated as a weighted mean, by the size of the industry

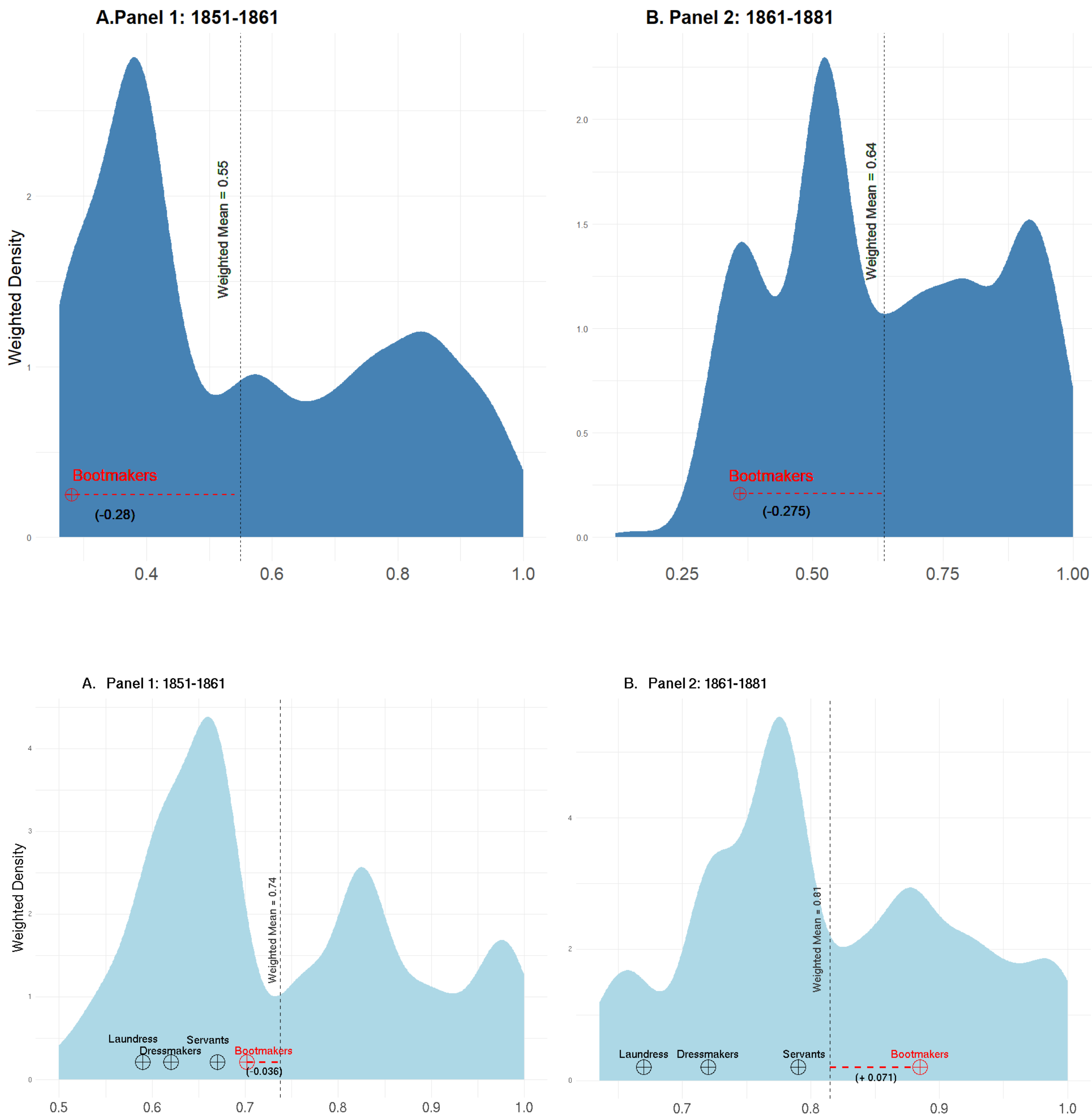


Figure 12: Distribution of Exit Rates, All Industries

Note: Data derived by author from ICeM census records. Top panel: Male. Bottom panel: Female.

In the bottom panel of Figure 3, we see that the mean exit rate for women is universally high. It is, naturally, higher in the second panel, which covers 20 years (1861-1881), but, compared to men, it is very high in both. This is unsurprising. The 19th century is the era of "separate spheres" and of the male breadwinner - women had a radically different relationship to the labour market than did men. Women worked less, and often left the labour market to have children. The absolute value of the female rates of exit are therefore to be expected. What is of interest is the shift of the position of female bootmakers vis-à-vis the national average and within the distribution of exit rates for women in other industries.

In the first period, prior to the technological shock, female bootmakers have an exit rate which is slightly below the mean for women. In the second panel, as the technological shock hits, the exit rates of female bootmakers increases by a full 10 percentage points. This marks a substantial rise. It is one that is anomalous when compared with change in exit rates in other industries. The divergence experienced by female bootmakers is located in the extreme right tail of that distribution.

To enrich the visualization and provide context, three other large industries are plotted in the bottom panel of Figure 3. These show the exit rate for dressmakers, domestic servants, and laundresses. None of these industries experienced a technological shock during this period, and their position in the distribution, vis-à-vis mean exit rates, does not change dramatically over time.

6.9 Appendix I: Reporting on Female Labour Force Participation

Modern definitions of FLFP focus on women being "economically active" (Ortiz-Ospina, Tzvetkova & Roser, 2018). This includes self-employment, and in practice translates into the sale of goods or services in exchange for an income. In 19th century England the most comprehensive record of FLFP emerges from the decennial census records. Census enumerators in 1851 were instructed: "The occupations of women who are regularly employed from home, or at home, in any but domestic duties, to be distinctly recorded instructions given to the census takers" (Shaw-Taylor & Wrigley, 2007, p.4). These instructions can form the basis of a definition of

FLFP for the period. The census likely under-records part-time employment, given the emphasis on "regular employment". In practice this may impact more on the accounting of female labour force participation

Can we trust the recording of women's LFP in the English census data of the 19th century? The controversy over whether the Victorian census records reliably report female employment is long standing. In a recent article, Edward Higgs revisits the historiography of the debate (Higgs & Wilkinson 2016). Several scholars have argued that the census records cannot be trusted (Higgs 1987; Hill 1993; Horrell & Humphries 1995; Sharpe 1995; Davidoff & Hall, 2002; Kay 2006). Higgs traces the origin of this argument to his own 1987 paper, and points out that subsequent papers espousing the position either cited his work or did not provide evidence to back up the claim: "In summary, it seems that the assumption that the work of Victorian women in the British censuses is under enumerated relies to a worrying extent on the comments made by me some thirty years ago, which I subsequently repeated in my guide to the census records, Making Sense of the Census in 1989" (Higgs & Wilkinson 2016).

The paper then summarizes a few of the arguments put forward in support of the reliability of the census records. Both John McKay and Michael Anderson note that the census records show higher employment for married women in Lancashire than in other counties (McKay 1998; Anderson 1999). Leigh Shaw-Taylor has argued that, if married women were well recorded it is unlikely that unmarried women would have been less well recorded.

In revisiting the debate Higgs notes both his original views and counter-arguments. Firstly, he had claimed that women occupied in part-time work were likely to have been excluded from the census records, and that this would have impacted particularly on women working in agriculture. He now notes that the seasonal labour done in agriculture is likely to have been under-reported for both men and women. Secondly, he points out that he relied heavily on ideological grounds, the Victorian views on "separate spheres", to suggest that census enumerators may have systematically undercounted women in employment. Finally, his original paper relied on a set of very local studies of the CEBs. These often made use of the records of a small employer, or those held in a local community. He feels now that these are likely not representative, and presents case studies which explore the limitations of these datasets.

He asserts that he has now changed his views, and considers the Victorian census records a reliable account of female employment. He then presents new empirical work by his co-author, Amanda Wilkinson, in support of the new view. Wilkinson makes use of occupation data given in asylum records from the towns of East Anglia. She matches individuals, and then compares occupation given in both sets of records. By 1871 the occupations have high match rates, ranging from 70%-100%, with match rates increasing over time.

Another two defences of the value of the census records of female employment have been put forward elsewhere. Leigh Shaw-Taylor points out that many of the papers arguing that women's work is not well recorded are in fact concerned with women's part-time and irregular work. This is clearly under-recorded. However, that does not imply that full time employment has been under-reported. A close study of the CEB records in one county, Herefordshire, provides evidence that women's work was not under-recorded (McGeevor, 2014). Textile work, in both the factories and in the cottage industries, was well recorded (Shaw-Taylor & Wrigley, 2007).

It is worth noting that the entire debate on these questions has taken place prior to the digitized version of the Victorian census data becoming available. Researchers often made use of the tables published in the 1851 census report. This provides summary tables of female occupation. There are 196 categories , recorded in 5 year age intervals. 21 of these are not linked to market-oriented work. Higgs and Wilkinson note that as ICeM becomes available it will become possible, for the first time, to examine women's work at the national level.

6.10 Appendix J: Regional Level DID

In this section I focus on changes in exit rates at the county level. In the previous section we compared exit rates of bootmakers against exit rates for non-bootmakers. We did this for men and women, in two different time periods. This provides a clear picture of what is happening at the national level. However, the national level results could mask variation at the more local level. In particular, it might be possible that the minimal labour displacement seen at national level conceals labour displacement in some areas of the country.

I run the specification below for each county in England, and convert the coefficients of interest into odds ratios. Here below I map the log odds ratio. Please see Appendix E for tables reporting on the coefficient of interest for each county [15].

$$\log\left(\frac{P(\text{Exit}=1)}{1-P(\text{Exit}=1)}\right) = \beta_0 + \beta_1^{s,t}\text{Bootmaker} + \epsilon \tag{5}$$

Once again, the left hand side is the probability of an individual exiting their industry, and Bootmaker is a dummy variable, allowing us to compare outcomes for bootmakers against individuals in all other industries. In Figure 4, below, I show the likelihood of a male bootmaker leaving bootmaking compared to men in other industries. I do this for both Panel 1 and Panel 2.

[15] At the moment the county level regressions are run without controls

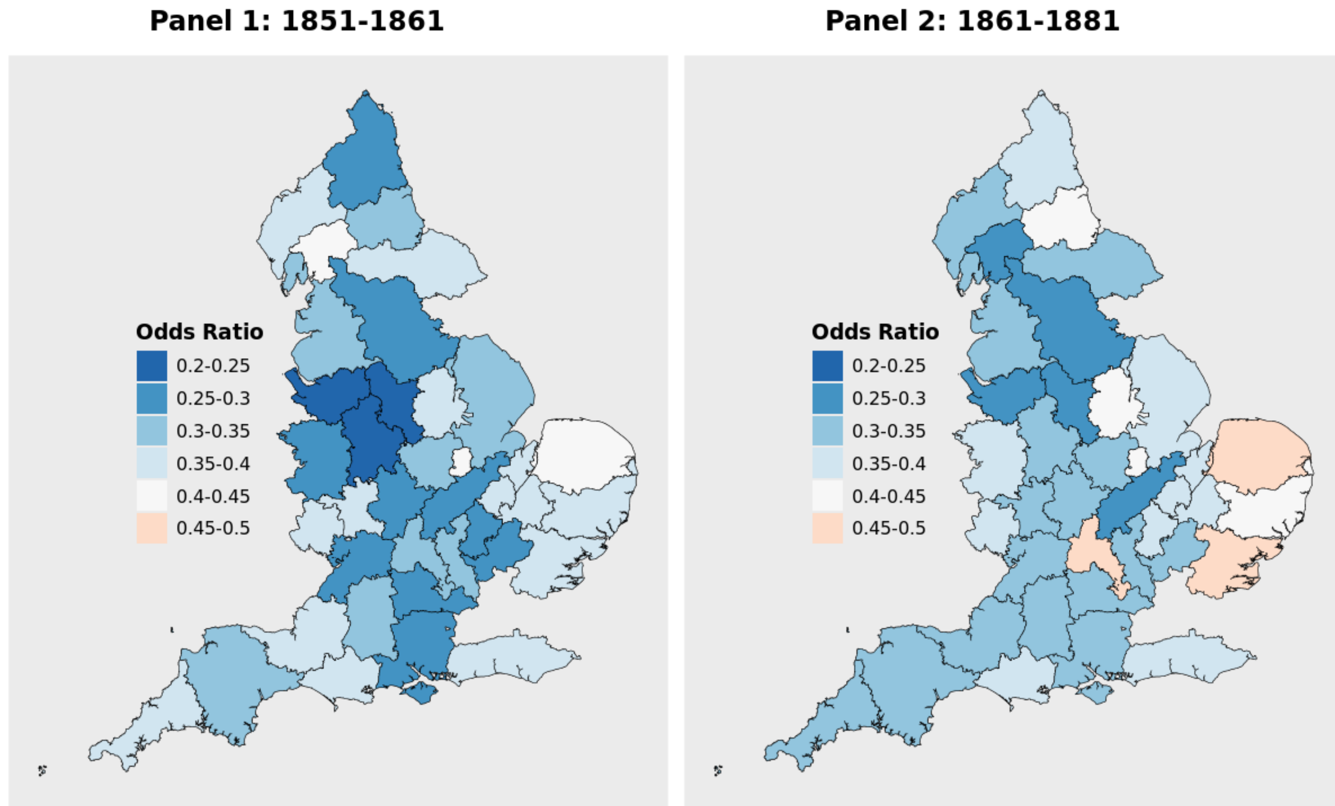


Figure 13: County Level, Men in Panel 1 and Panel 2
Source: data derived by author from ICeM census records. Please refer to Appendix E for more detail.

6.11 Appendix K: Human Capital Map

These are the dictionaries given the the clerks hired by the GRO to assign individuals to the correct industry. As you can see, the structure of the bootmaking industry evolves considerably over the years.

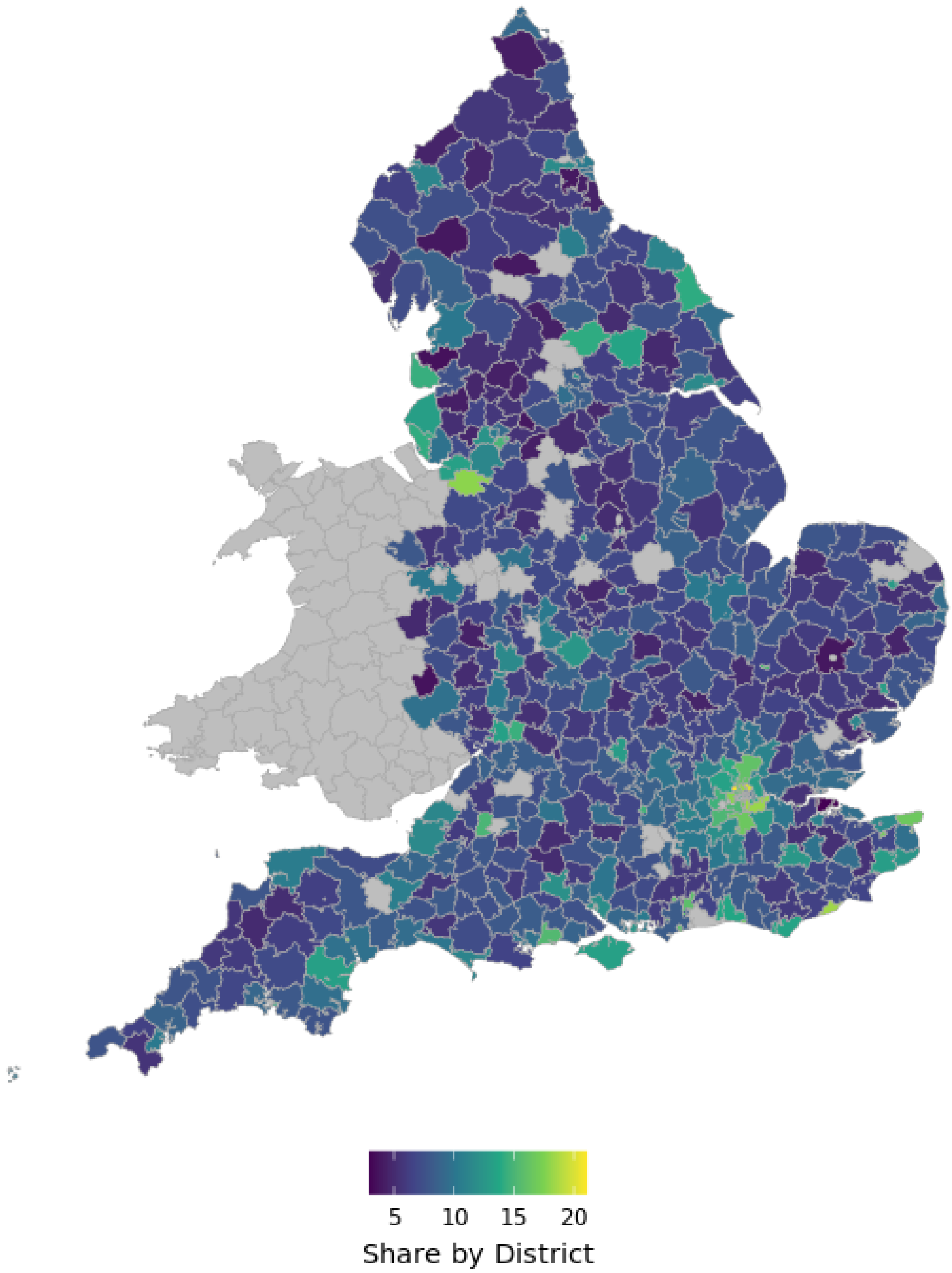


Figure 14: Human Capital Map

6.12 Appendix L: Dictionaries

These are the dictionaries given the the clerks hired by the GRO to assign individuals to the correct industry. As you can see, the structure of the bootmaking industry evolves considerably over the years.

ORDER 18.

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278. GLOVER, GLOVE MAKER.

Glove Knitter ; Glove Dyer ; Glove Spring Maker ; Boxing Glove Maker.
Cloth, Cotton, Lace, Silk, Thread, Worsted, Kid, Lamb, Leather, and all kinds of Glove Maker, Importer.

Cloth, &c., Gloves:
Cutter.
Sewer (Hand and Machine).
Pointer.
Welter.
Buttoner.
Finisher.
Inflater.

Leather Gloves:
Washer.
Egger.
Stainer.
Staker.
Parer.
Doler.
Sorter.
Cutter.
Puncher.
Thumb and Fourchette Cutter and Puncher.
Trimmer.
Folder.
Sewer (Hand and Machine).
Ironer.
Layer out.
Dresser.
Edge Blacker.

279. BUTTON MAKER, DEALER.

Button Mould and Counter Turner. Button Borer, Carder, Closer, Coverer, Driller, Flat Cutter, Mottler, Netter, Raiser, Stamper, Shanker, Setter.
Bone, Cloth, Gilt, Glass, Horn, Ivory, Leather, Linen, Metal, Military, Pearl, Silk, Wood—Button and Stud Maker.

280. SHOE, BOOT—MAKER, DEALER.

Boot and Shoe Manufacturer, Importer.
Boot and Shoe Man, Lift (Shoe Heel) Maker, Cutter.
Boot and Shoe Top, or Upper Manufacturer.
Boot and Shoe Tip, Plate, Heel Parer, Caster, Grinder, Glazer, Maker. Bow, Peg, Rosette Maker.
Carpet, List, Canvas, Shoe and Slipper—Binder, Maker, Dealer.
Ladies' Shoe man.
Last and Boot Tree Maker.
Boot and Shoe Lace, Dozener, Tagger—Maker, Dealer.
Shoe Mercer, Shoe Mercery Manufacturer.

Boot and Shoe Making:
Batchelor.
Beater-out.
Bottom Finisher.
Buffer.
Burnisher.
Channeller.
Cordwainer.
Cordwinder.
Cobbler.
Dresser, Repairer, Translator.
Edge Setter.
Levant Finisher, Dresser.
Levanter.
Sander.
Stock Fitter.
Vamp Cutter.
Clicker.
Closer.
Closer (Machine).
Binder.
Blocker.
Paster.
Paste Fitter.
Rough Stuff Cutter.
Putter-up.
Laster.
Leather Ranger.
Snob.
Sole-sewing Machine Operator.
Operator (Blake's, Whitmore, and Keats' Sewing Machine).
Rounder and all Rounder.
Pressman.
Sprigger.
Rivetter.
Tacker.
Nailer.
Finisher.
Flowerer.
Sew-round Hand.
Spring Fitter (Elastic).
Boot Plate Fitter.
Boot Front Blacker.
Boot Protector Maker.
Packer.
Warehouseman.

281. PATTEN, CLOG MAKER.

Clog Iron, Calker, Patten-Ring Maker, Clogger, Sabot Maker. Clog Clasper. Clog Seatsman.

282. WIG MAKER, HAIR DRESSER.

Artist in Hair.
Barber.
Chignon Maker.
Coiffeur.
Device (Hair) Maker, Worker.
Frizette Maker.
Hair Pad Maker.
Hair Roller Maker.

283. UMBRELLA, PARASOL, STICK—MAKER, DEALER.

Fan Maker.
Umbrella, Umbrella and Parasol Rib, Frame, Cap, Furniture, Tip, Maker. Notch Turner, Maker. Umbrella Rib Hardener. Umbrella and Parasol Coverer, Mender, Trnslator. Stick Cutter, Stainer, Paragon Cutter, Roller. Fish Skinner. Sun Shade Maker.

Figure 15: Dictionary 1871

6.13 Appendix M: Sons of Bootmakers

Table 9: Share of Sons of Bootmakers who Become Bootmakers

	1851	**1861**	**1881**
[l]Adult Bootmakers	220K	226k	197k
Sons of Bootmakers <19 y.o.			
1851	–	–	–
1861	28.4%	–	–
1881	26.2%	25.1%	–%
1891	–	22.8%	28.6%
1901	–	–	30%
1911	–	–	24%

Note: This table is based on collecting all sons of bootmakers under the age of 19 in the starting census year who are living with their family. Those sons are then linked forward into future years, and the share which are bootmakers is then calculated. Accordingly, the table above relies on seven panel datasets of Father-Sons pairs, which have been linked forward. Matching rates are 20%-22%.